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A Doctoral Thesis

Safety Impact of Connected and Autonomous Vehicles on Motorways: A Traffic Microsimulation Study

by

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Abstract

Connected and Autonomous Vehicles (CAVs) promise to improve road safety greatly. Despite the numerous CAV trials around the globe, their benefit has yet to be proven using real-world data. The lack of real-world CAV data has shifted the focus of the research community from traditional safety impact assessment methods to traffic microsimulation in order to evaluate their impacts. However, a plethora of operational, tactical and strategic challenges arising from the implementation of CAV technology remain unaddressed. This thesis presents an innovative and integrated CAV traffic microsimulation framework that aims to cover the aforementioned shortcomings.

A new CAV control algorithm is developed in C++ programming language containing a longitudinal and lateral control algorithm that for the first time takes into consideration sensor error and vehicle platoon formulation of various sizes. A route-based decision-making algorithm for CAVs is also developed. The algorithm is applied to a simulated network of the M1 motorway in the United Kingdom which is calibrated and validated using instrumented vehicle data and inductive loop detector data. Multiple CAV market penetration rate, platoon size and sensor error rate scenarios are formulated and evaluated. Safety evaluation is conducted using traffic conflicts as a safety surrogate measure which is a function of time-to-collision and post encroachment time. The results reveal significant safety benefit (i.e. 10-94% reduction of traffic conflicts) as CAV market penetration increases from 0% to 100%; however, it is underlined that special focus should be given in the motorway merging and diverging areas where CAVs seem to face the most challenges. Additionally, it is proven that if the correct CAV platoon size is implemented at the appropriate point in time, greater safety benefits may be achieved. Otherwise, safety might deteriorate. However, sensor error does not affect traffic conflicts for the studied network.

These results could provide valuable insights to policy makers regarding the reconfiguration of existing infrastructure to accommodate CAVs, the trustworthiness of existing CAV equipment and the optimal platoon size that should be enforced according to the market penetration rate.

Finally, in order to forecast the conflict reduction for any given market penetration rate and understand the underlying factors behind traffic conflicts in a traffic microsimulation environment in-depth, a hierarchical spatial Bayesian negative

binomial regression model is developed, based on the simulated CAV data. The results exhibit that besides CAV market penetration rate, speed variance across lanes significantly affects the production of simulated conflicts. As speed variance increases, the safety benefit decreases. These results emphasize the importance of speed homogeneity between lanes in a motorway as well as the increased risk in the motorway merging/diverging areas.

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1 Introduction

1.1 Background

In 1864, an Austrian-Hungarian inventor, Siegfried Marcus, created the first gasoline powered combustion engine and used it to propel a vehicle (American Society of Engineers, 2014). Since then, vehicles have brought a revolution in transport and have radically changed the structure of society. Vehicles are undoubtedly the most widespread means of transport, and reports show that the past four years have seen an increase of 16% in the number of registered motorised vehicles globally (World Health Organisation, 2015). More specifically, in Great Britain there has been a steady increase in the number of licensed vehicles since the end of the second World War (Department for Transport, 2015) .

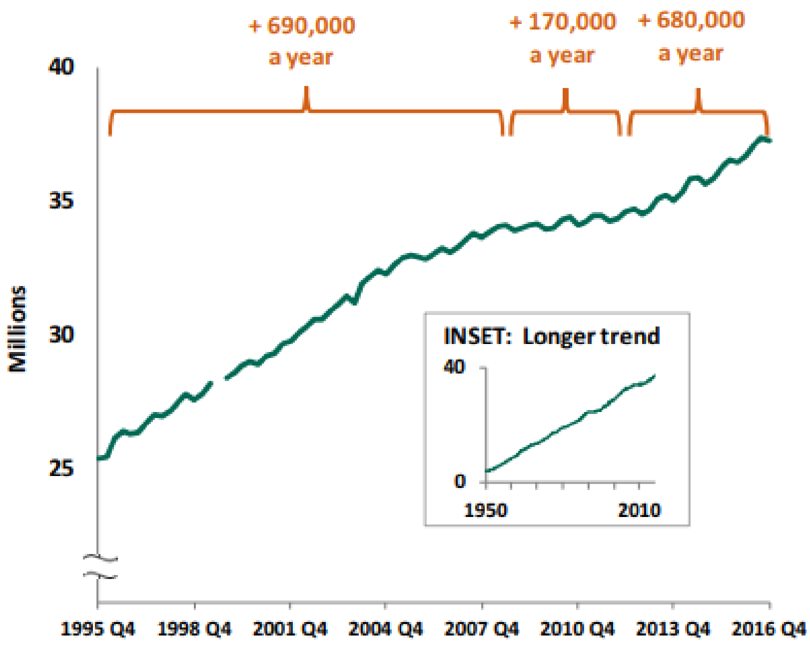


Figure 1.1 Number of licensed vehicles in Great Britain (source: DfT, 2015)

Inevitably, the expansion of the vehicle fleet has led to severe consequences on road traffic, environmental pollution and road safety. The number of road traffic deaths is “unacceptably high” (i.e. 1.35 million every year worldwide) and road accidents are expected to become the fifth leading cause of deaths worldwide by 2030 according to World Health Organisation, (2018).

Several infrastructure-based and vehicle-based technologies, also known as Intelligent Transport Systems (ITS), have been developed over the last decades in order to mitigate the negative effects of vehicle growth on traffic flow and efficiency, safety and the environment (Eskandarian, 2012).

The Connected and Autonomous Vehicle (CAV) is the latest progress of ITS and it is a technology that has advanced significantly over the past few years and an increasing number of real-world tests are taking place worldwide.

Even though a significant amount of effort has been put into CAV research and industrial development, the concept of CAV has existed for a few decades already. Humanity had envisaged self-driving cars in science fiction films and cartoons. For example, in 1958, Disney air a show where autonomous vehicles could navigate coloured highways lanes and that were operated with addresses coded on punch cards. A couple of decades later, in the mid 1980's, the underlying technology and computational methods in order to achieve this vision of CAVs started becoming available (Anderson *et al.*, 2014). Since then, in the last 25 years, the evolution of CAVs can be taxonomised into three groups that correspond to significant waves of developmental gains.

The first wave of development included the so-called foundational research attempts (Anderson *et al.*, 2014) and lasted from 1980 to 2003. In this wave, CAVs were tested on highways, and mainly or partly relied on existing infrastructure for guidance. One major demonstration of this wave took place in 1997 in California's I-15 highway near San Diego, where eight CAVs were guided by magnets embedded in the highway and coordinated with vehicle to vehicle (V2V) communication (Ioannou, 1998). It is worth noting connectivity among CAVs was considered an important factor and was investigated from the early stages of CAV development. A more advanced example of this wave, was the vision, based vehicle developed by Bundeswehr University Munich which navigated at speeds of 100 kilometres per hour without traffic (Lantos and Maarton, 2011).

The second wave of CAV development can be placed between 2003 and 2007 where three "Grand Challenges" relating to CAVs were launched globally. The aim of first two challenges was to develop a fully autonomous vehicle that could navigate in a 150-mile off-road racetrack. Unfortunately, no vehicle was able to complete the full stretch of the first challenge and the best attempt completed less than eight miles of the course (BBC News, 2004). Five vehicles completed successfully the second challenge in 2005, a fact which indicated that important lessons were learnt by the first challenge. Most importantly, in 2007, DARPA held its third and final CAV challenge where the vehicles were asked to navigate through a 60-mile urban course while obeying traffic laws and navigating along other autonomous and human-driven vehicles. Six participating vehicles were able to finish the race while some of them received penalties for violating traffic rules. After this challenge it became obvious that sensor systems and computing algorithms involved in CAVs needed to mature further in order to detect and react to the behaviour of other vehicles, to navigate marked roads and to obey traffic rules and signals.

The second wave of advancements and especially the “Grand Challenges” sparked the creation of partnerships between automotive manufacturers and the research/academic sector and motivated the automotive sector to advance CAVs. Since 2010, there is a plethora of CAV projects worldwide. Namely, Google’s Driverless Car initiative has brought CAVs from laboratories and confined spaces into commercial research (Waymo, 2016). Major automotive manufacturers and operators such as Uber, Audi, Toyota, Ford and Peugeot are involved in CAV development and testing projects and are starting to test their vehicles in the real-world (iMove Australia, 2020).

As the deployment of CAVs in the road network is expected to bring about a radical overhaul in existing transport systems, this disruptive technology has attracted a great deal of interest from original equipment manufacturers (OEMs), governmental and local authorities and the academia. CAV technology has potential to revolutionise our economy and society by reducing traffic congestion, road traffic crashes and vehicle emissions (Fagnant and Kockelman, 2015).

In order to prove these benefits, the vast majority of automotive manufacturers work towards collecting operational data and are testing CAVs in the real world in both motorways and urban environments (e.g. Waymo project (Waymo, 2016), NUtonomy trials in Singapore, Google car in California, UK Smart Mobility Lab at Greenwich, Lutz Pathfinder in Milton Keynes). These trials have proven that CAVs will introduce a range of unprecedented challenges and will bring a multifaceted transformation to the existing road network. For example, whether existing motorway and urban infrastructure can accommodate CAVs is yet to be fully elucidated. Additionally, the communication standards and a unified protocol between existing infrastructure technology and CAVs have not been clarified yet. Furthermore, the inherent challenges arising from the interaction between human driven and connected and autonomous vehicles during the transition period are largely unknown (Reich, 2013). Even the compatibility between software of different CAV manufacturers is still uncertain and this might affect their operations and co-operative decision making at a corridor or a network level (Anderson *et al.*, 2014)..

1.2 Research Problem

The numbers associated with road safety are staggering. Even though the number of road traffic deaths relative to the size of world population has stabilized over the past 3 years, the raw number of road traffic deaths continues to climb each year. Road traffic accidents now represent the eighth leading cause of death globally claiming 1.35 million lives and 50 million injuries and possibly almost every one of those deaths and injuries is preventable (World Health Organisation, 2018) as 94% of the crashes include a form of human error as a contributing factor (Singh, 2015).

One could argue that by taking the human out of the driving equation, the corresponding percentage of accidents would be eliminated as CAVs are a technology which aims to perform the driving task without the help of the human driver. Indeed, several studies have performed meta analyses on traffic accident data in order to estimate the percentage of accidents that would be reduced if CAVs were to be introduced in existing traffic streams. They usually conclude that CAVs are expected to decrease road traffic crashes by approximately 90% at high market penetration rates (e.g. Fagnant and Kockelman, 2015). However, such an estimate might be false or misleading as this kind of approach does not consider important technological and operational CAV challenges such as sensor errors and failures that will arise when CAVs are employed.

Indeed, the real-world testing so far of autonomous driving have proven that these aforementioned challenges might lead to devastating results. CAVs have been involved in a number of accidents already (The New York Times, 2016; Green, 2018) which have costed the lives of pedestrians and the passengers of the vehicle itself. Inevitably, these events have not helped to persuade the public regarding their reliability. It is obvious that these challenges need to be addressed and evaluated prior to the implementation of CAVs in the real world.

Perhaps the only way to do that is by applying an ex-ante evaluation method. One of the most widespread evaluation methods that have been applied in the past in order to evaluate the safety impact of a traffic-related technology, is traffic simulation. This method is flexible and has a lot of potential. However, the major drawback associated with CAV simulation is the fact that it is *unknown* how exactly CAVs will function in the real world. More specifically, the exact driving behaviour is widely unknown due to data unavailability and macroscopic characteristics of CAV traffic flow are not possible to predict, as they depend on various factors connected with software and hardware specifications.

Existing studies have tried to address this surrounding uncertainty by attempting to develop a number of representative scenarios which arise according to logical assumptions, the vision of the corresponding authors or speculations about how CAVs will operate in the future. The question of whether these scenarios cover the realistic range of challenges of CAVs cannot be possibly answered.

The fact that simulating CAVs is a complex task, adds to already existing research problems mentioned above. Each CAV is a complex entity consisting of multiple subsystems (i.e. sensing, perception, planning and control subsystem) that need to be simulated in order to address the challenges arising from the different types of road network layout. Due to this inherent complexity, a number of studies has attempted to simplify things by simulating only one or two of the aforementioned subsystems such as the control subsystem which includes fundamental elements of CAV control such as the longitudinal control algorithm (ATKINS, 2016a; Jeong, Oh and Lee, 2017; Rahman and Abdel-Aty, 2018). However, such simplifications involve only individual vehicle kinematic characteristics in the analysis and do not consider inherent uncertainties at strategic, tactical and operational levels arising from the rest of the CAV subsystems. On the other hand, by attempting to simulate all CAV subsystems accurately with a combination of simulators, other studies developed highly detailed

CAV simulation frameworks which were too computationally heavy to be tested at a large scale and consequently unable to provide useful recommendations regarding the possible future CAV implementation strategy (Figueiredo *et al.*, 2009; Noort, Arem and Park, 2010; O'Hara *et al.*, 2012). Finding the fine balance between these two approaches described above would be the key to provide useful results and at the same time address challenges arising from the nature of CAVs.

This thesis attempts to address the aforementioned methodological issues by developing an integrated CAV simulation framework which covers a number of challenges arising from the subsystems of CAVs. The developed framework is applied in a large scale simulated motorway environment and the results are discussed from a simulation and statistical point of view in order to obtain an in-depth understanding of the challenges and factors affecting the safety in a motorway during the transition from the fully manual vehicle era to the fully autonomous era. The results provide useful policy recommendations that could potentially facilitate the adoption of CAVs in existing road networks and traffic streams.

1.3 Research Significance

As mentioned above, the number of casualties due to road accidents is high and CAVs promise to reduce these numbers by approximately 90% by taking over the driving task at high automation levels. However, this estimation has yet to be confirmed using real-world data.

It is impossible to confirm this estimation in the real world according to a recent study (Kalra and Paddock, 2016). Using real-world data to verify the safety benefits of CAVs is impractical as of today, because hundreds of millions of miles, or in some cases hundreds of billions of miles of real-world CAV operational data are needed to obtain statistical evidence of potential safety benefits. This amount of data would take several decades to be collected (Kalra and Paddock, 2016). As a result, similarly to the ex-ante evaluation era of other transport interventions (e.g. variable speed limits, high occupancy vehicle/toll lanes and adaptive cruise control) research has focused on identifying alternative methods to assess the impacts of CAVs.

Simulation is perhaps the only alternative appropriate method for studying complex systems that are inaccessible through direct observation and real-world measurement (Lamotte *et al.*, 2010). However, in order to sufficiently cover the challenges arising from CAVs and to understand the factors associated with their safety impact, CAVs need to be simulated in a wide range of scenarios. In this regard, this research attempts to cover a number of representative scenarios arising from major challenges associated with their technological and operational challenges and understand in depth the underlying factors affecting CAV safety so as to provide useful insights to policy makers to develop the optimal CAV implementation strategy.

1.4 Aim and Objectives

The aim of this PhD project is to quantify the safety impact of CAVs on motorways using a traffic microsimulation framework.

In order to achieve this aim, the following research objectives are formulated:

- To identify likely impacts and issues affecting safety of CAVs in mixed traffic streams;
- To explore and review techniques used to evaluate the impact of Intelligent Transport Technologies and CAVs;
- To formulate a traffic microsimulation framework capable of simulating CAVs along with human-driven vehicles;
- To analyse the data from the microsimulation for the purpose of evaluating the impact on safety of CAVs;
- To assess underlying factors affecting the occurrence of traffic conflicts in a traffic simulation environment using a statistical approach
- To recommend a number of specific scenarios where the safety benefit of CAVs would be maximized, specifically during the transition period.

1.5 Thesis Outline

This thesis consists of seven chapters. An outline of the chapters is provided below:

- **Chapter 2** conducts an extensive literature review in order to clearly define CAVs and identify potential impacts and issues arising from their implementation in the real world;
- **Chapter 3** conducts a methodological review of studies investigating the impact of intelligent transport systems related to CAVs in order to identify potential candidate methods for CAV evaluation. Additionally, current CAV simulation approaches are discussed along with methods to evaluate safety in a traffic microsimulation environment. Finally, the potential use of statistics in CAV safety evaluation is investigated;
- **Chapter 4** presents the methodology of this thesis. The chapter starts with a description of the traffic microsimulation framework. Following, the conflict identification algorithm is described. The final section of this chapter describes the statistical method employed;
- **Chapter 5** describes the different sources of data used for the purpose of this thesis and presents the results of the calibration and validation process of the simulation platform;
- **Chapter 6** shows and critically discusses the results derived from the simulation and statistical models developed. This chapter also discusses practical implications and policy recommendations arising from the analysis;
- **Chapter 7** summarises this research project and outlines its contributions to knowledge and limitations/assumptions. Finally, recommendations for future research are discussed.

2 Literature Review of the Impacts of CAVs

2.1 Motivation

CAVs is undoubtedly a technology that is under the microscope of the media. This sudden popularity has led to the transmission of various positive and negative messages to the public regarding their direct and indirect impacts. For instance, stories about accidents with CAVs have reached the headlines of newspapers and websites quickly, ultimately affecting the opinion of the society (The Guardian, 2016). However, these stories usually fail to provide a comprehensive analysis of the accidents or incidents with regards to equipment failure, environmental conditions or the exact reason of the accident due to lack of background CAV knowledge.

Hence, in order to get a wholistic understanding and develop an appropriate methodology for this research, it is of utmost importance to initially define them, describe their main elements; sensors, functionalities and control mechanism (subsystems), and subsequently summarise their potential issues and impacts. Therefore, the first part of this literature review chapter defines CAVs and describes their most important features. The second part summarises potential issues arising from the introduction of CAVs and impacts of CAVs found in existing literature in order to obtain a wider perspective for the evaluation framework designed in this thesis.

2.2 Connected and Autonomous Vehicles

This part of the literature review aims to describe the most important features of a CAV in the following sections:

- **Definition and Automation Levels**. The various automation levels according to National Highway Traffic Safety Administration (NHTSA) are defined.
- **Existing Automation Functionalities**. The second section includes the description of the existing automation functionalities such as Adaptive Cruise Control, Lane Changing Assistance and Parking Assistance.

- **Equipment in CAVs.** The equipment used in CAVs is presented in the third section.
- **V2X Communication.** CAV’s ability to communicate with vehicles and infrastructure are analysed and the equipment used to achieve that are described.
- **Control Mechanism.** Finally, the most common control mechanisms of the CAV are presented in the final section.

2.2.1 Definition and Automation levels

Connected and Autonomous vehicle, also known as driverless, self-driving or robotic vehicle is a vehicle equipped with an autopilot system which allows it to safely move from one place to another without help from a human driver (Liden, 2013). It must be noted that the term autonomous is sometimes used interchangeably in the literature with the term automated. However, looking into the etymology of these two words, the following can be concluded:

a) Automated-automatic: The origin of this word comes from the ancient Greek word **αὐτόματος** (aftomatos) which means something that is being done without external intervention or something that is being done or occurring spontaneously, without conscious thought or attention. This is not the case for CAVs as the decisions are taken using artificial intelligence and attention to detail;
b) Autonomous: The origin of this word comes from the ancient Greek words **εαυτός** (eaftos) – self and **νόμος** (nomos) – law. It means something that has the freedom to govern itself or control its own affairs – having the freedom to act independently. In the case of a CAV, the subsystems contain the laws that rule its operation.

According to the above definitions the term autonomous is used in this thesis. However, when relevant literature mentions the term automated, the term automated is used for consistency purposes.

In 2013, the National Highway Traffic Safety Administration of the U.S. Department of Transportation released a policy which defines the various levels of vehicle automation, ranging from vehicles which are not equipped with automated control systems at all (automation level 0), to fully automated vehicles (automation level 5) (National Highway Traffic Safety Administration, 2013a).

More specifically:

- **Level 0 – No-Automation**. The driver is in full control of the driving task. Vehicles that are equipped with driver support/convenience systems, also known as Advanced Driver Assistance Systems (e.g. Collision warning systems), are also considered as "level 0";
- **Level 1 – Driver Assistance**. In this level of automation, the vehicle can automatically assume limited authority over one primary control (such as adaptive cruise control). The driver still has overall control and is solely responsible for safe operation but can choose to hand limited authority over a primary control to the vehicle;
- **Level 2 – Partial Automation**. In this automation level, one primary control function (steering and acceleration) is designed to work autonomously, in order to relieve the driver of their control. The driver is responsible to monitor the roadway and safety operation and is expected to be available to take over the driving task and any given time on short notice;
- **Level 3 – Conditional automation**. Vehicles at this level of automation have full control of monitoring of the driving environment. Vehicles can monitor these conditions and can require transition back to driver control. The driver is expected to be available to occasionally take over the driving task;
- **Level 4 – High automation**. Vehicles at this level of automation are capable of performing all safety-critical driving functions and monitoring roadway conditions for an entire trip. They can perform dynamic driving manoeuvres such as changing lanes. They require the driver to input the destination of the trip but not to be available to take control at any time during the trip. The limitation of this automation level compared to automation level 5 is that it can operate in certain driving environments (e.g. motorways);

- **Level 5 – Full automation.** Vehicles of this automation level are equipped with a full-time automated driving system which controls all aspects of dynamic driving under all environmental/roadway conditions.

2.2.2 Existing vehicle-based Automation functionalities

The driver assistance systems mentioned in NHTSA's vehicle automation classification discussed above, are more widely known as Advanced Driver Assistance Systems (ADAS). They can exist in different combinations in vehicles. According to Pijpers (2007), some of the most widespread ADAS are:

- **Lane Change Assistant**: The lane change assistant is an ADAS which detects the lane as well as all other vehicles surrounding the ego vehicle and warn the driver during a lane change process;
- **Lane Keeping Assistant**: This system detects the lane and gives feedback to the driver if he is leaving a predefined trajectory within the lane. A video image processing system is used to detect the lane;
- **Automatic Parking**: The automatic parking is a function which helps the driver during the parking procedure. It can take full control of the steering wheel and engine during a parallel parking manoeuvre;
- **Pre-Crash Collision and Mitigation System**: These pre-crash systems, which were implemented first by Toyota and Honda, aim to reduce the potential damage of an accident by pre-tensioning the safety belts when an imminent collision is detected which cannot be avoided;
- **Obstacle and Collision Warning and Avoidance**: This system aims to first warn the driver if a potential collision with another vehicle or obstacle is detected and take control of the vehicle in emergency situations in order to avoid an accident. The system takes over longitudinal and lateral control during the critical time when the dangerous event takes place;
- **Platooning**: A platoon consists of a group of several vehicles (usually three or more) which are connected electronically and follow one another closely. An example of platooning is trucks connected in order to save space, fuel and increase road network performance;

- **Adaptive Cruise Control/ Stop and Go**: This system is responsible of keeping a safe distance from the preceding vehicles especially in congested conditions. For their operation, they depend heavily on a range of active sensors such as laser/radars/lidars.

2.2.3 Equipment in CAVs

Undoubtedly, reliability is a fundamental requirement of the existing automation functionalities as they control important functions of a vehicle. In order for existing automation functionalities to make a safety related decision, data must be collected and evaluated. CAVs are equipped with a range of sensors which sense, “think” and act on behalf of the driver (Pijpers 2007).

The most widespread CAV sensors are the following:

1. **Radar: Ra**dio **D**etection **a**nd **R**anging, is a machine which transmits strong radio waves to detect, range and map objects. In existing automation functionalities, the most frequently used Radars are of the Pulse-Doppler variant;
2. **Lidar: Li**ght **D**etection **a**nd **R**anging, or Laser Imaging Detection and Ranging is a technological instrument which uses laser pulses to determine distance to an object or surface. The most significant difference between radar and a lidar is that the latter cannot detect dynamic information about the detected objects such as velocity. Lidar also uses a much shorter wavelength of the electromagnetic spectrum, has a larger detection range and a wider field of view than the radar;
3. **Infrared Camera:** An infrared camera is a camera which is sensitive to heat radiation of objects. In that way, it can detect heat-emitting objects such as vehicles or human beings;
4. **Vision:** A vision system is a device which collects light on a light sensitive backplate to detect objects within its vision range. Lately, the use of digital cameras has dominated the vision component of the sensors.

Table 2.1, presents which aforementioned equipment is used in section’s 2.2.2 “Existing Vehicle-based Automation Functionalities”.

Table 2.1 Equipment Used in Existing Automation Functionalities

	Lane Change Assistant	Lane Keeping Assistant	Automatic parking	Pre-Crash Collision and Mitigation System	Obstacle Collision Warning and Avoidance	Platooning	ACC
Radar	•	•	•	•	•		•
Lidar	•	•	•	•	•		•
Infrared Camera						•	
Vision	•	•		•		•	•

2.2.4 V2X Communication

CAVs are equipped with communication devices in order to communicate with Infrastructure, known as Vehicle to Infrastructure communication (V2I) and with other vehicles, known as Vehicle to Vehicle communication (V2V). CAVs need to communicate with both infrastructure and other vehicles in order to receive and transmit useful traffic information such as incidents, queue formation, speeds and speed limits. Communication consists of technological instruments and network architecture.

The technology used, can be divided into the following categories (Belarbi et al, 2003):

- Systems that reuse existing infrastructure GSM/UMTS (Global system for Mobile communications/Universal Mobile Telecommunication Service);
- Dedicated Short-Range Communication (DSRC);
- Global Positioning Systems (GPS/Galileo);
- Satellite Digital Service Broadcasting (S-DSB);

The architecture of the communication system can be split into three categories (Belarbi et al, 2003):

- **Infrastructure dependent communication system:** This system architecture provides stable and uniform service to the properly equipped vehicles along the road segment that it can cover;
- **Ad-hoc network (WiFi)**: Also known as VANET (Vehicular Ad-Hoc Network) Wireless (WiFi) networks are created dynamically, depending on the vehicles circulating the road network. The vehicles in a road network are used as wireless routers/nodes to create a wide network. VANET can provide the participating vehicles with traffic data and it can support cooperative driving functions such as lane insertion;
- **Mixed (structured and ad-hoc networks):** Mixed networks keep the advantages of infrastructure and ad-hoc communication systems architecture. Both vehicle to vehicle communication is used and transmitters which are installed directly in the infrastructure, communicate with vehicles as well as Traffic Operation Centres.

2.2.5 Control mechanism

With the technological equipment being described in the previous section, the question remaining to be answered is: how does all this technology cooperate to drive the car without the need of a human driver?

Campbell et al. (2010) summarising their experience of the 2007 DARPA (Defence Advanced Research Projects Agency) Urban Challenge (DUC), state that most of the participants developed their driverless vehicle by dividing the control mechanism into four different subsystems, each of them controlling an important function of the vehicle: sensing, perception, planning and control.

- **The sensing subsystem's** purpose is raw data gathering. Vehicle data such as lateral and longitudinal position are gathered by GPS and lane and road geometrical measurements are gathered by radars, lidars and cameras;
- **The perception subsystem** is responsible to translate the raw data received by the sensing subsystem, to useful information about the vehicle, such as vehicle location within a lane, other vehicles' locations or longitudinal position of own vehicle in the road network;

- **The planning subsystem**, for most of the challenge participants, includes common components such as path planners, behavioural planners and route (map) planners, although there were variations across the teams. The planning subsystem played an important role in reasoning about the probabilistic information coming from the perception subsystem;
- **The control subsystem** included the actuators and commands to drive the car. Information about the control law would come by combining information of the higher-level planning (planning subsystem) and direct sensing to increase speed of response.

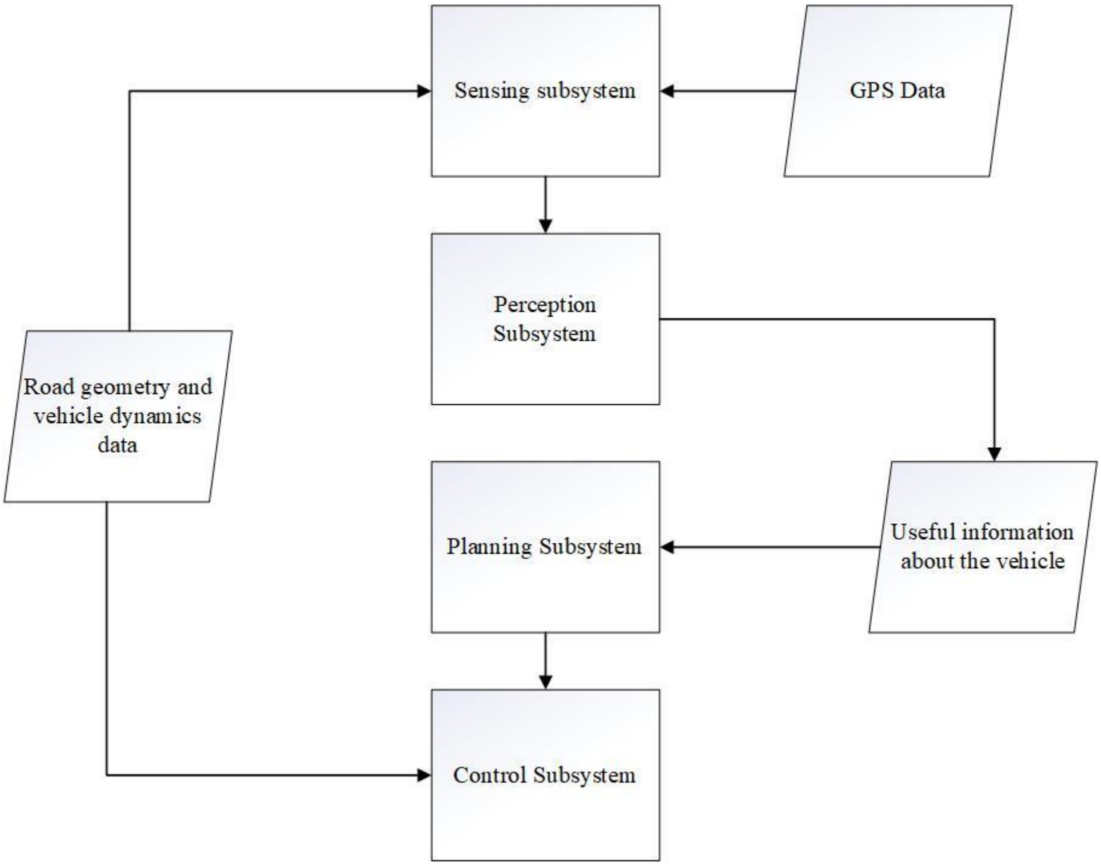


Figure 2.1 Flowchart of the control Mechanism of an Autonomous Vehicle

Perhaps the most important subsystem of a CAV which is also the key to autonomy is the planning sub-system. This subsystem involves planning algorithms incorporated in the middleware of CAVs' navigation, situation understanding and decision-making modules. The main purpose of planning is to calculate a collision-free path towards the destination of the vehicle while taking into account the vehicle's kinematic characteristics, its manoeuvre capabilities in a mixed traffic environment, the traffic rules and road boundaries (Zhang *et al.*, 2013). Planning is a computationally heavy process which takes place in parallel with other functions of the CAV. The input of the planning is usually data coming from the sensors of the CAV which are supplemented with data coming from digital road maps in order to optimise the planning process. In more detail, in order for the planning sub-system to plan the journey for the CAV, the surrounding environment needs to be translated from data coming from its sensors to a configuration also known as a state space. The state space consists of vehicle dynamics measurements such as position, orientation, velocities etc. As the vehicle advances in a road network, the information from the sensors and the digital maps are converted into a digital representation of the road network which is a mandatory requirement of the planning subsystem. This virtual representation is also known as the search space.

The planning algorithms which exist in CAVs come from the field of robotics and have been subsequently applied in different on and off-road vehicles. Planning algorithms in CAVs can be divided into four categories according to Varaiya, (1993):

a) Route planning which is the process of finding the optimal global route from point A to point B by potentially taking into account additional real-time traffic information
b) Path planning which is an important primitive for CAVs that calculates the shortest or optimal path between two points within a given road
c) Manoeuvre choice is a high-level decision-making system of the CAV which performs an action that would alter the position and speed of the vehicle on the road. The manoeuvre usually is performed for safety reasons while also taking into account the path that is specified from path planning
d) Trajectory planning (used interchangeably with the term control planning) is the real-time planning of the actual vehicle's transition from one feasible state to the next, satisfying the vehicle's kinematic limits based on the vehicle dynamics and constrained by the navigation comfort, lane boundaries, traffic rules and obstacles in the road network (Katrakazas *et al,* 2018). Most existing trajectory planning algorithms initially follow trajectories generated in a low resolution/lower dimensional search space and subsequently, the resulting

optimal trajectory smoothed out on a higher resolution/ higher dimensional search space.

Once the search space is constructed in a virtual environment in the CAV planning sub-system the planning algorithms are employed in order to select the best path, behaviour and trajectory.

According to Katrakazas *et al.*, (2015) the planning process can be divided into three levels of planning:

1. Identification of the best geometric path for the vehicle to follow
2. Identification of the best manoeuvre to perform
3. Identification of the best trajectory to follow by optimising geometric curves according to kinematic constraints

One practical example of the above process is the route between two points. The route planner identifies and constructs the geometric path of a vehicle which consists of several waypoints. The way from one waypoint to another must be free of obstacles and the vehicle must be able to interact with other vehicles while navigating between them. According to the potential obstacles and the interaction with other vehicles, the CAV can decide to perform certain manoeuvres such as overtaking, turning or braking in order to reach the next waypoint. If the waypoints and the proper manoeuvre are calculated by the CAV then the trajectory planning describes the procedure by searching the best way to connect the determined way points (Katrakazas *et al.*, 2015).

In order to put this section in the framework of this thesis, one should consider the capabilities of the primary method used. The previous paragraphs, emphasised that in order for the CAV to apply its planning algorithms it should be provided with a clear search space (a virtual representation -usually in 3D) which is a product of the data coming from its sensors such as a lidar and a camera. Unfortunately, such visual data are not available within traffic microsimulation which is the primary method used in this thesis. In more detail, in microscopic simulation, vehicle routes are pre-defined and manoeuvres and ultimately the trajectories of vehicles are calculated based on a set of pre-defined rules contained in the car following and lane-changing algorithms overarching the control of the vehicle. However, the exclusion of the realistic trajectory and path planning algorithms does not hinder the validity of the results, as CAVs are approached from a more macroscopic point of view. Hence, this thesis will focus mostly on the car-following and lane-changing behaviour which will be considered as a sufficient approximation of the planning and control sub-system of a CAV.

2.3 Potential Impacts and Issues of Connected and Autonomous Driving

2.3.1 Introduction

One of the most unanimous statements regarding CAV implementation is that CAVs are going to bring great benefit to all aspects of the society (Fagnant and Kockelman, 2014; Milanes and Shladover, 2014). However, how are CAVs going to affect the different impact areas? In order to answer this question, one should first identify the new issues and challenges arising from the implementation of CAVs in the road network. Additionally, the question of which impact areas -precisely- are CAVs going to affect is yet to be answered. For this reason, a number of studies has focused on taxonomizing the impacts of CAVs (Fagnant and Kockelman, 2015; Milakis *et al.*, 2015; Hörl *et al,* 2016). Most of these studies categorize the impact areas in direct (1st order) or indirect impacts (2nd or 3rd order) based on how they occur. For example, Milakis *et al.*, (2015) imply that with the introduction of this new vehicle in the network, the direct impacts would be traffic implications such as road capacity and congestion, travel cost implications, and travel choice implications. Consequently, through a ripple effect, each of these first order impacts would lead to several other second order impacts such as infrastructure implications, land use and vehicle implications. Ultimately, areas such as safety, economy, air pollution, energy consumption, public health and social equity are going to be affected.

From the above, it is obvious that there is a plethora of interrelations and “rebound effects” (one impact area affecting -even negatively- another impact area) between impact areas and this is a big challenge when trying to taxonomize the impact of CAVs and furthermore when trying to evaluate the actual impact. For this reason and also due to method and data availability, the majority of existing literature has focused on three main impact areas (traffic, safety and environment) following the approach of “ceteris paribus” (all else equal) meaning that for instance, the safety impact is evaluated while the rest of the parameters or impact areas (e.g. traffic demand) remain unchanged. Evaluating multiple impact areas at a time would increase the complexity of the projects significantly as the interrelation between impact areas and how they will occur are largely unknown.

The available literature and the methodologies that are analysed in Chapter 3 of this thesis made clear that this literature review chapters should focus on three main impact areas: Safety, Traffic and Environment. Due to the aim of this thesis, special focus is given on safety. Additionally, in order to obtain a deeper understanding of the motivation of existing literature current issues arising from the implementation of CAVs are discussed in each section. Finally, societal implications of CAVs regarding public acceptance, legislation and liability are also summarised briefly. It must be noted that the scientific papers and reports cited in this chapter are not criticised from a methodological point of view. This is done in chapter three of this thesis.

2.3.2 Safety

According to recent studies, CAVs have the potential to dramatically improve road safety. The safety benefits include mitigating crash severity and decreasing the possibility of crashes, (Gurney, 2014; Poczter and Jankovic, 2014; Rodoulis, 2014) by eliminating the human factor which is the primary cause of crashes in 94% of the cases according to NHTSA (Singh, 2015). Table 2.2 summarises potential causes of 5.5 million crashes in the U.S. It is also noticeable that some combinations of factors (i.e. alcohol, driver distraction, drugs and fatigue which are shown in bold characters in the table) are responsible for causing a 40% of the fatal crashes (Fagnant & Kockelman 2015). In their paper, the authors speculated that autonomous vehicles would reduce fatal crashes by at least 40% as they would not be susceptible to human failings. This reduction however does not reflect the crashes caused by speeding, aggressive driving, inexperience, slow reaction time, inattention and other human driver faults.

Table 2.2 U.S. crash motor vehicle scope and selected human and environmental factor involvement source: (Fagnant & Kockelman 2015) (edited)

Total crashes per year in U.S. (National Highway Traffic Safety Administration, 2013b)	5.5 million

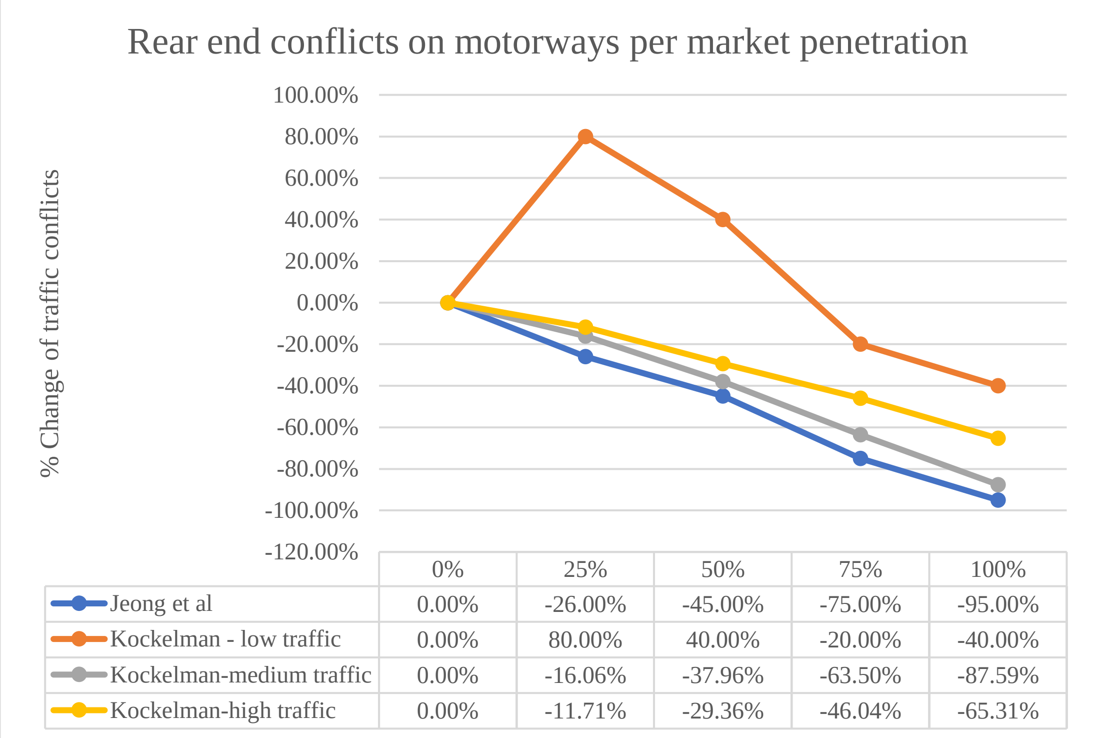
Total fatal and injurious crashes per year in U.S. (National Highway Traffic Safety Administration, 2013b)	2.22 million
Fatal crashes per year in U.S. (National Highway Traffic Safety Administration, 2012)	32,367
% human cause as primary factor (National Highway Traffic Safety Administration, 2008)	93%
% of fatal crashes involving alcohol (National Highway Traffic Safety Administration, 2012)	31%
% involving speeding (National Highway Traffic Safety Administration, 2012)	30%
% involving distracted driver (National Highway Traffic Safety Administration, 2012)	21%
% involving failure to keep in proper lane (National Highway Traffic Safety Administration, 2012)	14%
% involving failure to yield right-of-way (National Highway Traffic Safety Administration, 2012)	11%
% involving wet road surface (National Highway Traffic Safety Administration, 2012)	11%
% involving erratic vehicle operation (National Highway Traffic Safety Administration, 2012)	9%
% involving inexperience or overcorrecting (National Highway Traffic Safety Administration, 2012)	8%
% involving drugs (National Highway Traffic Safety Administration, 2012)	7%
% involving ice, snow, debris, or other slippery surface (National Highway Traffic Safety Administration, 2012)	3.70%
% involving fatigued or sleeping driver (National Highway Traffic Safety Administration, 2012)	2.50%

% involving other prohibited driver errors (e.g. improper following, driving on shoulder, wrong side of road, improper turn, improper passing etc) (National Highway Traffic Safety Administration, 2012)	21%

In the same study, it is estimated that the safety benefit of autonomous vehicles would depend on the market penetration rate, predicting a 50% reduction in crash rate and a 50% reduction in injury rate at the 10% CAV market penetration rate. The authors additionally predict 90% reduced crash and injury rates at the 90% market penetration rate. By using Insurance Institute for Highway Safety's accident data, a similar estimation is achieved by Anderson et al. (2014) who predict a 39% reduction in crash fatalities during the fully automated era. Unfortunately, the results of the above studies cannot be compared directly as different performance indicators are used (crash/injury rate vs number of crash fatalities).

Without providing exact predictions on the safety impact of autonomous vehicles, Ni & Leung (2014) speculate an analogy of automated aviation technologies with CAVs. They imply that since automated aviation technologies reduced aviation accidents, autonomous vehicles will possibly improve road safety. Finally, Kim et al. (2015) state that, ideally, when the penetration rate of autonomous vehicles reaches 100% accidents could be reduced to zero.

More recently, studies have focused on traffic simulation in order to estimate the safety impact of CAVs. Motorways are arguably the simplest road network layout, (no interaction with other road users such as pedestrians etc) and this is the reason why most studies focus their efforts on this type of network (Kockelman and Hanna, 2016; Jeong, Oh and Lee, 2017). Both studies used rear end and lane changing traffic conflicts as an indicator of safety. Traffic conflict is defined as an event involving two or more moving vehicles approaching each other in a traffic flow situation in such a way that a traffic collision would ensue unless at least one of the parties performs and evasive manoeuvre (Parker and Zegeer, 1988). The results of these studies are not necessarily comparable due to differences in the underlying CAV control algorithms, network parameters (number of lanes, number of merging and diverging areas) but for good measure they are summarised in Figure 2.2. The results for Chen et al's study seemed to be similar to the observations of Jeong et al. for medium to high traffic flow volumes. However, a big change is observed in low traffic flow value's in Chen's study.



	0%	25%	50%	75%	100%
Jeong et al	0.00%	-26.00%	-45.00%	-75.00%	-95.00%
Kockelman - low traffic	0.00%	80.00%	40.00%	-20.00%	-40.00%
Kockelman-medium traffic	0.00%	-16.06%	-37.96%	-63.50%	-87.59%
Kockelman-high traffic	0.00%	-11.71%	-29.36%	-46.04%	-65.31%

Figure 2.2 Traffic conflicts change % on motorways per market penetration rate (0%, 25%, 50%, 75%, 100%)

Furthermore, motorway related studies have used several other surrogate safety measures to evaluate safety such as Time to Collision (TTC) and its derivatives, Time Exposed Time-to-Collision and Time Integrated Time-to-collision (Jeong, Oh and Lee, 2017; Li *et al.*, 2017a; Rahman and Abdel-Aty, 2018). The results of these studies once again are based on the assumptions and the configurations of their experiments and are not comparable. Hence, listing the actual results would be in vain without a reference value. However, in summary, all the above studies proved that CAVs will bring a great safety benefit to a motorway network.

Despite the encouraging results, new, unprecedented concerns arise from the implementation of CAVs. Numerous studies express fears about hardware and software reliability and the protection against potential malicious attacks from hackers. The ability of a CAV to recognise quickly and reliably objects in the roadway is often challenged in the literature (Dalal and Triggs, 2005; Farhadi *et al.*, 2009; The

Economist, 2012). The difficulty does not rely on the task of recognising an object solely, but on the extremely small margin for error (Fridman, Jenik and Reimer, 2016). An object in a roadway may be small or large, with various heights, a human on the road can be walking, sitting or lying down resulting in a partially obscured view. Vasic & Billard (2013) identify faulty electronic parts and loose connections across parts as a reason leading to accidents during human-robot interaction. Furthermore, weather conditions of snow, fog and reflective road surfaces from rain and ice or even a bright sky can create challenges for sensors and driving operations.

An unfortunate example of a sensor failure is the crash occurred with a Tesla's automated vehicle in July, 2016 (The Guardian, 2016). In this particular crash, the car's sensors failed to detect a large white 18-wheel truck and trailer crossing the highway, against a bright sky, which resulted in the death of the driver of the automated vehicle. Figure 2.3 strongly supports these concerns of CAV safety as a percentage of disengagements from autonomous driving mode according to the Waymo's annual disengagement report happened due to strangely looking objects or aggressively moving vehicles.

Thankfully, despite the aforementioned concerns, results so far seem encouraging as Fridman et al. (2016) state that CAVs would be able to predict their failures as technologies reach higher readiness levels. For instance, as far as disengagements are concerned, there is a noticeable decline according to the Waymo's annual disengagement report (Waymo, 2016). Specifically, the disengagements per thousand miles in 2016 were reduced to 0.2 compared to 0.8 in 2015.

Furthermore, a plethora of papers raise awareness about what would happen if bugs would occur in CAV software (Pinto, 2012; Vasic and Billard, 2013; Ni and Leung, 2014; Schellekens, 2015; Kelly *et al.*, 2016). For instance, Schellekens (2015) brings up the example of a fatal accident due to a software bug in a non-Automated Toyota vehicle. Vasic & Billard (2013) seem to agree as they identify programming bugs and faulty algorithms as causal factors behind accidents in Human-Robot interactions. Furthermore, Pinto (2012), Ni & Leung (2014) and Kelly et al. (2016) state bugs as a potential barrier to CAV implementation. In fact, this concern is proven by the annual disengagement report of Waymo (Waymo, 2016). As Figure 2.3 shows, a significant percentage of the disengagements from autonomous driving happened due to a software discrepancy.

	Cause of disengagement	2015	2016	2017	2018
1	Weather conditions	0	189	189	55
2	Road surface conditions	0	0	0	21
3	Software discrepancy	0	51	51	734
4	Hardware discrepancy	0	0	0	171
5	Reckless user	20	10	10	78
6	Control discrepancy	0	170	170	35407
7	Perception discrepancy	95	132	132	402
8	Manual takeover	0	0	0	54888
9	Testing	687	1443	1443	185
10	Localisation discrepancy	0	4	4	555
11	System fault	8	2	2	23
12	Geometric configuration	0	0	0	4
13	Motion trajectory planning	0	96	96	1047
14	Communication	0	0	0	2380
15	Indeterminable	0	0	0	58
16	Construction zone	17	2	2	1
17	Debris in roadway	0	2	2	0
18	Lane detection	111	0	0	5

Figure 2.3 Cause of disengagements from Autonomous driving mode.

Furthermore, knowing where the autonomous mode failures happen would be valuable to vehicle manufacturers and researchers. The majority of the disengagements happen in complex urban environments “streets” as mentioned in Figure 2.4.

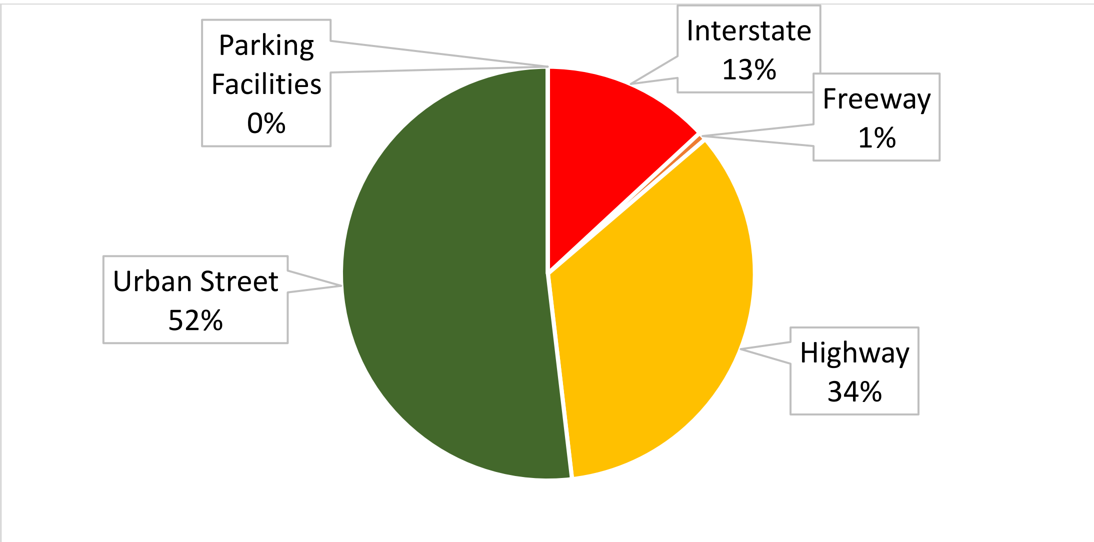


Figure 2.4 Location of disengagements from Autonomous driving mode

Finally, studies express concerns about cyber security (Ni & Leung 2014.; Petit & Shladover 2014; Litman 2015). More specifically, Fagnant & Kockelman (2015) mention that transport policy makers, automotive manufacturers and future CAV drivers often worry about electronic security. Computer hackers, disgruntled employees and terrorist organizations could be potential threat to the implementation of CAVs, as they could use CAVs to create traffic disruptions and cause collisions. In the worst case scenario according to Fagnant & Kockelman (2015), someone could develop a two-stage virus in which they could control an entire fleet of vehicles for two weeks and then use them in order to cause a massive nation-wide catastrophe. In their conclusions, the authors are however being optimistic, stating that U.S. have managed to maintain a secure, large, critical, national infrastructure system including power grids and air traffic control systems which could possibly extend to CAVs. In addition, Pinto (2012) acknowledges the hacking problem in CAVs and describes the solution as keeping the CAV as isolated as possible from outside inputs.

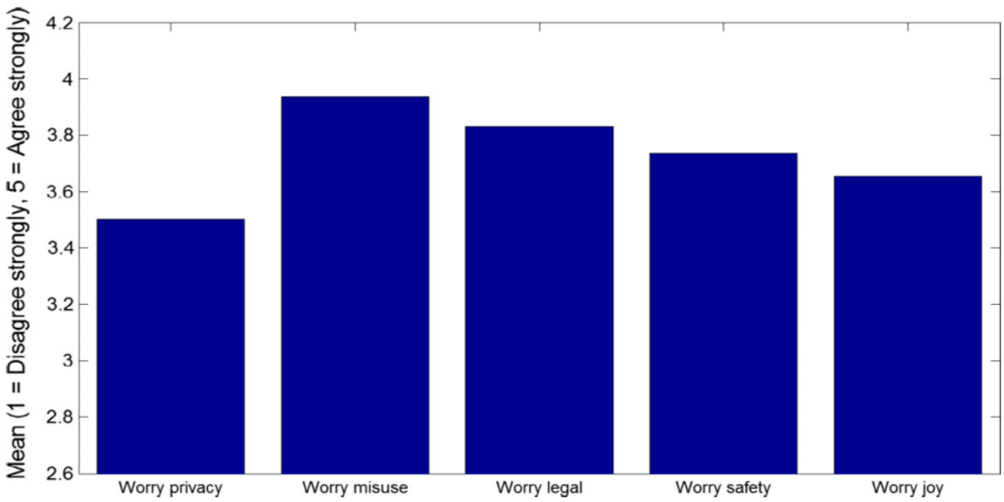


Figure 2.5 Mean response on a scale from 1 to 5 regarding respondents worries about Fully Automated Driving (Kyriakidis, Happee and Winter, 2015)

A study conducted by Kyriakidis et al. (2015) investigating user acceptance, concerns and willingness to buy CAVs, seems to agree with the previous paragraph, highlighting cyber security and misuse of CAVs as the first public concern. As it can be seen in Figure 2.5, most of the respondents agreed that misuse and safety are in the top 3 concerns regarding CAVs, a finding that is also in line with Schoettle & Sivak (2014).

As perfect as autonomous vehicles can be, accidents may never be eliminated completely, even during the fully automated era because simply "systems fail" as it is argued by Smith (2012). Additionally, safety problems, not known yet to CAV developers, may emerge in the following years.

2.3.3 Traffic

CAVs have the potential to improve traffic in different ways. Shared Autonomous Vehicles (SAVs) could provide inexpensive mobility on-demand services and could play a vital role in sustainable transport systems (Krueger, Rashidi and Rose, 2016). CAVs could mitigate congestion by reducing vehicle ownership levels substantially (Burns 2013; Fagnant et al. 2015;)

Additionally, literature suggests that connected automation has proven to be effective in preventing shockwave formation and propagation under certain assumptions

(Talebpour and Hani S Mahmassani, 2016). Berg & Verhoef (2016) argue that autonomous vehicles can safely drive closer together than cars driven by humans, thereby possibly increasing road capacity, reducing travel time and delays. Furthermore, autonomous vehicles will be able to seamlessly merge into moving traffic and then exit the highway with ease (Forrest, Konca and Ovp, 2007). However, literature raises a concern about a potential increase in roadway capacity may lead to side effects such as users switching to autonomous vehicles may alter their behaviour with respect to departure time (Berg and Verhoef, 2016). Finally, parking is also a traffic related problem that the implementation of autonomous vehicles could help addressing. By being able to park themselves to a more distant location and come back when they are needed, autonomous vehicles could eliminate the time spent in 'searching for parking' and relieve roadway congestion in city centres (Forrest *et al*, 2007; Zhang *et al.*, 2015).

A number of attempts to quantify the impact on traffic via predictions have been made. The chronologically first studies on the specific subject predicted a reduction in congestion delay from 1-15%, 21-39% and 60-100% at the market penetration rates of 10%, 50% and 90% accordingly (Atiyeh 2012; Shladover et al. 2012; Fagnant & Kockelman 2015). However, the aforementioned studies assume that the traffic impacts of CAVs are identical with the impact of CACC (Cooperative Adaptive Cruise Control) on traffic. Additionally, Tientrakool et al. (2011) estimated a 43% highway capacity increase if all vehicles use sensors alone and a 273% capacity increase if all vehicles use vehicle-to-vehicle communication and sensors.

More recent studies also predict improvement in traffic congestion using several key performance indicators such as level of service, capacity, traffic throughput and stability. In addition, once again, significant differences are observed in the underlying assumptions of the studies as well as their network configurations. Therefore, the results cannot be compared directly (Roncoli, Papageorgiou and Papamichail, 2015; ATKINS, 2016c; Shi and Prevedouros, 2016; Talebpour and Hani S. Mahmassani, 2016). However, in order to obtain a sense of the magnitude of the impact of CAVs on traffic, the results of the two most comprehensive studies in terms of road network and key performance indicators are summarised below.

Talebpour & Hani S. Mahmassani (2016) predicted an increase in traffic throughput. As the market penetration rate of connected and autonomous vehicles increased, the traffic throughput (vehicles/hour/lane)) increased up to 3,250 vehicles per hour per lane. This represents a significant increase from the average capacity of a motorway lane of 2,100 vehicles/hour/lane.

Finally, ATKINS (2016) used traffic microsimulation to conclude regarding traffic impacts of CAVs. They tested various market penetration rates as well as different driving environments (urban – Strategic Road Network motorway). Their results showed a significant reduction in average delays, journey times and journey time variability. Their results are summarised in Figure 2.6 and Figure 2.7. Special attention should be given to Figure 2.6. In the lowest CAV market penetration rate, an increase in average delay is observed. This might be due to the interaction between CAVs and human-driven vehicles causing slight turbulences in the traffic flow. However, in general, the results seem encouraging.

Scenario	Average delay (s)		Average journey time (s)		Journey time variability[20] (s)		Coefficient of variation[21]	
	(s)	%	(s)	%	(s)	%		%
Base	35.84	-	539.79	-	20.17	-	0.0374	-
(1) 25% CAV	36.17	*+0.9%*	538.49	*-0.2%*	19.38	*-3.9%*	0.0360	*-3.7%*
(2) 50% CAV	33.39	*-6.8%*	533.62	*-1.1%*	17.65	*-12.5%*	0.0331	*-11.5%*
(3) 75% CAV	29.77	*-16.9%*	527.72	*-2.2%*	15.33	*-24.0%*	0.0291	*-22.3%*
(4) 100% CAV	23.72	*-33.8%*	517.77	*-4.1%*	10.52	*-47.9%*	0.0203	*-45.7%*
(5) Upper bound	21.38	*-40.3%*	479.29	*-11.2%*	9.14	*-54.7%*	0.0191	*-49.0%*

Figure 2.6 Estimated traffic improvement due to CAVs at different penetration rates – motorway environment source: (ATKINS, 2016)

Scenario	Average delay (s)		Average journey time (s)		Journey time variability (s)		Coefficient of variation	
	(s)	%	(s)	%	(s)	%		%
Base	65.91	-	277.78	-	88.38	-	0.3182	-
(1) 25% CAV	57.70	-12.4%	219.52	-21.0%	19.74	-77.7%	0.0899	-71.7%
(2) 50% CAV	54.44	-17.4%	205.35	-26.1%	10.01	-88.7%	0.0488	-84.7%
(3) 75% CAV	51.89	-21.3%	198.72	-28.5%	7.24	-91.8%	0.0364	-88.6%
(4) 100% CAV	48.02	-27.1%	192.64	-30.7%	6.00	-93.2%	0.0312	-90.2%
(5) Upper bound	46.36	-29.7%	184.25	-33.7%	5.71	-93.5%	0.0310	-90.3%

Figure 2.7 Estimated traffic improvement due to CAVs at different penetration rates – urban environment source: (ATKINS, 2016)

2.3.4 Environment

Global carbon emission from fossil fuels have significantly increased since 1900 and more recently carbon dioxide emissions from fossil fuels have increased by about 90% since 1970.

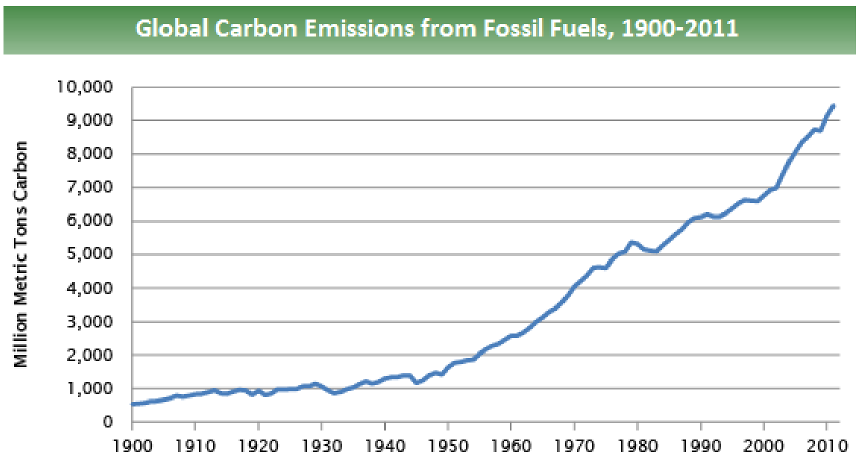


Figure 2.8 Global Caron Emissions from Fossil Fuels, 1900-2011 (source: International Energy Agency)

According to the International Energy Agency, transport is the second largest sector in terms of emissions contributor releasing 22% of global CO_2 emissions in 2011 and global transport fuel demand is expected to grow by nearly 40% by 2035 (International Energy Agency, 2015). Autonomous vehicles have the potential to reduce emissions and save fuel (J M Anderson *et al.*, 2014; Rodoulis, 2014) by fundamentally changing car use. CAVs are speculated to be better than humans at throttle control with smaller acceleration/deceleration values, which can reduce fuel consumption and emissions significantly. However, there are very few quantitative analysis studies to confirm this hypothesis (Liu *et al.*, 2019);

A study performed by Mersky & Samaras (2016) using the Virginia Tech Comprehensive Fuel Consumption model and simulation, concluded that autonomous vehicles could save up to 10% fuel compared to conventional cars. In a similar manner, autonomous vehicles could reduce emissions and the reduction increases as the market penetration rate of autonomous vehicles gets higher according to Talebpour & Mahmassani (2016). Fagnant & Kockelman (2014), use an agent-based investigation of an urban shared autonomous vehicle paradigm which simulates the movement of travellers and their shared vehicles around a city throughout the day. Their framework allows the evaluation of the environmental impact of a shared autonomous vehicle fleet and they conclude that overall emissions savings are expected to be sizable. However, a final number is not given. Finally, Wadud et al. (2016) interpret CAVs' environmental impact by breaking it down to the impact of its different mechanisms/components. The results of the study are presented in Figure 2.9. According to the authors, vehicle right-sizing (increasing the average occupancy of vehicles) and vehicle platooning could decrease energy consumption by 20-50% and 3-25% respectively.

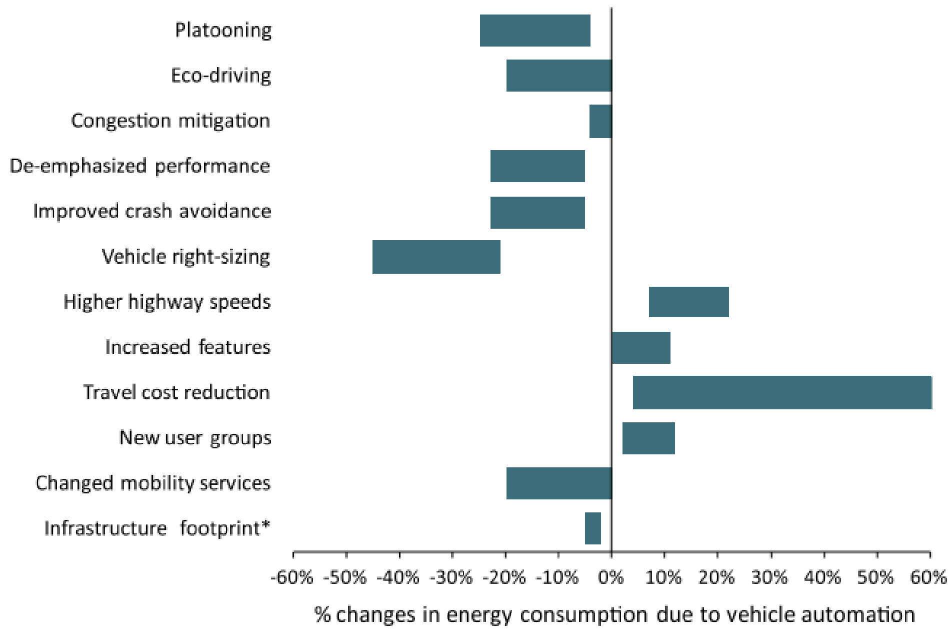


Figure 2.9 Summary of estimated ranges of energy impacts of vehicle automation through different mechanisms (source: Wadud et al. 2016).

2.3.5 Public acceptance, legislation and liability

With the anticipated benefits and concerns about CAVs discussed above, policy makers face a number of questions regarding the implementation of autonomous vehicles that still remain unresolved. Are consumers aware of the benefits or limitations of autonomous vehicles so that they might want to buy one? Who will be liable if/when a driverless vehicle crashes? What is the state of the current legislation about autonomous vehicles?

Acceptance

A-priori acceptability of fully autonomous vehicles and public opinion have been the topic of surveys conducted during the last couple of years (Payre, Cestac and Delhomme, 2014; Schoettle and Sivak, 2014; Kyriakidis, Happee and Winter, 2015). Payre et al. (2014) in their survey, state that 68.1% of their sample size (i.e. 421 French drivers) accept fully autonomous vehicles. Predictors of intention to use a fully autonomous car in their linear regression model, were mainly attitudes, contextual acceptability and interest in impaired driving, followed by driving related sensation seeking and gender. Also, highly important, according to the same study is the fact that most users would prefer to use a fully autonomous vehicle in Highways mainly, in traffic congestion or while parking. Kyriakidis' et al. (2015) survey analysed the responses of 5000 respondents from 109 countries. The results showed that most respondents find manual driving the most enjoyable mode of driving, yet they found the idea of fully automated driving exciting. Also, they were found to be concerned about legal issues. Finally, a survey conducted by Schoettle & Sivak (2014) compares public opinion about self-driving vehicles in different countries: China, India, Japan, U.S. the U.K. and Australia. The main findings of the study tend to agree with Kyriakidis et al. (2015), stating that the majority of the respondents had positive initial opinion about the technology and had high expectations of it. However, they expressed high levels of concern regarding safety issues, driving performance and self-driving commercial vehicles. Both studies also investigated the willingness to pay for the technology, concluding that the majority is not willing to pay extra for it.

What is not mentioned in the studies that are presented is the degree of the respondents' awareness of the benefits of autonomous vehicles and how well they are informed about the state of the art. In contrast to autonomous vehicles' accidents that are reaching the headlines of press with ease (Davies, 2016), publicly available information about CAVs' latest technological improvements is relatively limited. To prepare the society for such a change their advantages and disadvantages should be known and discussed.

Legislation

In order for manufacturers to be able to test autonomous vehicles, appropriate legislation should be in place. Fortunately, in most cities where the testing takes place, the legislation has been formed. More specifically, legislation concerning autonomous vehicle exists in some states of the United States (Legislative Council, 2011; Weiner and Smith, 2016) , the United Kingdom (BBC, 2013), France, Switzerland (Zurich) and Singapore. Nevertheless, according to their needs, every country has developed its own rules and laws about autonomous vehicles. The differences according to Lloyd (2014) include basic elements such as the definition of autonomous vehicles or more specific matters such as insurance, incident and disengagements from autonomous mode reporting, geographical and environmental limitations (type of road where can the autonomous vehicles be tested), completion of controlled testing, test-driver training requirements, and special license plates.

It is highly important that for such a sensitive matter as CAVs which affects road safety, an integrated, widely accepted legal framework should be formulated.

Liability

In a conventional crash, there are three primary possible causes (or a combination of them): the driver, a vehicle malfunction or unavoidable natural conditions. Any liability is usually allocated to the responsible part: the driver or the vehicle manufacturer. Inevitably, autonomous vehicles will change the dynamics of who may be held liable for an accident. (Marchant and Lindor, 2012). The underpinning theory behind autonomous vehicles consists of taking the human driver out of the driving equation. How can humans still be held liable for an accident though? In the current state of the art for example, humans are advised not to take their hands off the steering wheel even if the Automation Level 2-3 car is running on autonomous mode (The Guardian, 2016). If humans fail to follow the law and the instruction manual of the autonomous vehicle, they can still be held liable for an accident. That is not the majority of the cases though. According to Marchant & Lindor (2012), when an accident occurs with an autonomous vehicle , the vehicle manufacturer, or some other party involved in the design, manufacture, or operation of the autonomous vehicle is likely to be held liable for a high percentage of the accidents. The list of potential parties includes the vehicle manufacturer, the software engineer and the company responsible for the possibly faulty hardware parts. Gurney (2014) states that the current state of liability law will not be able to assign the blame for the accident to the party that caused it and he proposes a liability scheme that assesses fault based on the cause of autonomous vehicle accidents. Since autonomous vehicles will start circulating on the roads within a decade and the cars will inevitably cause accidents legal authorities should develop a liability scheme that will be able to assign the responsibility of the accident to the party who initially caused it.

3 Review of Methodological Approaches in Evaluation of Emerging Transport Technologies

3.1 Motivation

The motivation of this chapter is to identify the most appropriate methodology in order to achieve the aim of this thesis – to quantify the safety impact of CAVs on the motorway. CAVs are believed to be the next-generation technology for future societies. CAV evaluation research has evolved significantly over the last decade, however, there are plenty of areas in which CAV research can expand and mature. With this being said, there are still lessons to be learnt from existing methodological approaches that evaluate Intelligent Transport Technologies which are preceding to CAVs. Therefore, the first section of this chapter will try to identify methods applied for relevant to CAVs Intelligent Transport Systems evaluation in order to obtain a wider picture of the historically available and widely accepted methods. The second part of the chapter will review methodological approaches in CAV simulation.

3.2 Methods Applied for Intelligent Transport Systems Evaluation

In order to improve traffic flow, road capacity, road safety and to reduce vehicle emissions, several infrastructure and vehicle based technologies have been developed over the years. They are known as Intelligent Transport Technologies (ITT). In order to develop ex-ante and ex-post evaluations of these technologies, several techniques have been used depending on the nature of the examined technology. An ex-post evaluation consists of a systematic and objective assessment of a completed project, programme or policy regarding their planning, implementation and obtained results (OECD 2010). On the other hand, ex-ante evaluation studies aim to calculate the impact of a measure or technology before its implementation in the real world and possibly make recommendations for a better implementation strategy.

This section will identify the most widespread ex-ante and ex-post techniques that were used in the past to evaluate the impact of infrastructure and vehicle based ITS in order to relate the methodologies to a possible use in the evaluation of the safety impact of CAVs. Even though the aim of this PhD is to evaluate the safety impact of CAVs, this literature review chapter will also include studies which evaluate the impact of certain technologies on traffic characteristics which can be translated into safety results at a later stage. The technologies examined are:

• **Variable Speed Limits (VSL)**, is an Intelligent Transport System capable of improving the operations of freeway facilities under congested conditions by displaying variable speed limits on roadside variable message signs (Nissan & Koutsopoulos 2011). VSL aim to improve the safety of a freeway by reducing variances in speed (speed harmonization) and preventing shockwave formation (Ha et al. 2003). Autonomous vehicles also aim to improve safety in a similar manner, by reducing variances in speed by adopting a less aggressive driving behaviour and by being able to travel at as steady speeds as possible, forming vehicle platoons. This is the reason why VSL are examined in this chapter of the literature review.

• **High Occupancy Vehicle/Toll lane (HOV/HOT)**. HOV lane is usually the innermost lane of a motorway and vehicles are allowed to use this lane if they are manned with more than two (2+) or more than three (3+) passengers in some cases. The initial evaluation of HOV lanes showed the need to increase the lane throughput, without decreasing the benefit that they provide to car poolers. As a result, HOT lanes were introduced, which allowed single-occupant vehicles to use HOV lanes for a toll (Noland et al. 2016). A generalised concept of the HOV/HOT lanes are the Managed Lanes. Given that any new technology such as autonomous vehicles enters the market incrementally, the need for improved infrastructure will emerge. Reich (2013), proposes the use of designated lanes for use by vehicles with a specified level of technology (e.g. Autonomy level 3+). He states that as CAVs enter the traffic stream, the time will come when the designation of special lanes for these vehicles will be beneficial by limiting the danger in the interaction between autonomous and non-autonomous vehicles. However, he expresses his concern about the timing of the implementation. A too-early implementation of CAV only lane could bring quite the opposite of the expected effect. According to his predictions, a penetration rate of 50% which will be achieved by 2040, will be sufficient to implement dedicated CAV Lanes.

• **Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC)** are two widespread Advanced Driver Assistance Systems which aim to comfort drivers, by getting driving tasks out of their hands. ACC and CACC have been in development for more than ten years and aim to positively impact traffic efficiency and safety (Li et al. 2017). ACC was initially developed, which allowed vehicles to automatically adjust their speed to maintain a safe distance from preceding vehicles. CACC is an improved version of ACC which includes wireless vehicle-to-vehicle communication, (V2V) in order to further increase the traffic efficiency, safety and fuel consumption benefit. V2V communication also allows properly equipped vehicles to form platoons, vehicle groups travelling with travelling at the same speed very close to each other.

The methodologies identified through the literature review are summarised as follows:

1. "Before and after" studies

2. Statistical Modelling - forecasting

3. Traffic Simulation

3.2.1 Before and after studies

Extensive effort has been put into evaluating VSL by conducting before and after studies which are also known as intervention analyses. One of the prerequisites for this method to be applied is the data availability before and after the implementation of the intervention.

Initially, Highways Agency UK (2004) in their report on the M25 Controlled motorway which included a VSL measure, state that by analysing the data collected before and after the intervention, there was an 1.5% increase in traffic throughput over 5-hour peak periods, travel times became more reliable, there were 10% less injury accidents during the period of operation, 2-8% decreased emissions and improved fuel consumption.

On the other hand, a VSL application on a part of the A2 motorway in the Netherlands observed no capacity increase due to the VSL application, although, a smaller variance in headways was observed and a smoother traffic flow (van den Hoogen and Smulders, 1994). More recently, Papageorgiou et al. (2008) used the so-called fundamental speed- traffic flow diagram to examine the impact of mandatory VSL. They applied their method using flow-occupancy data from a European motorway before and after the implementation of VSL. They concluded that VSL reduce the slope of the flow-occupancy graph at under critical occupancies and shift the critical occupancy to higher values in the flow-occupancy diagram. Their results were inconclusive regarding flow capacity. In a similar manner, Nissan & Koutsopoulos (2011) prove that their proposed advisory VSL measure did not have any significant impact on traffic conditions, both immediately after its implementation and several months later. For their study, they analysed data from the E4 motorway in Stockholm before and after the implementation of VSL, using a two-regime flow-density model. However, this study did not examine the driver compliance to the displayed speed limit.

Quinn et al. (2000) summarises the preliminary evaluation surveys of Britain's first HOV 2+ lane, the A647 in Leeds. The results of the study showed that HOV journey times were reduced from 8 to 6 minutes for a 5km trip, a relative journey time saving of 25%. Although, journey times for non HOVs increased but they are still lower than for trips using parallel routes and a diversion (8%) into parallel routes was observed. Kwon & Varaiya (2008) evaluate the effectiveness of California's HOV 3+ system using peak hour traffic data from loop detectors over many months before and after the implementation of the system. By calculating the traffic flow, average speed and travel times they concluded that the implemented HOV lanes: were under-utilized with 81% of HOV detectors measuring flows below 1400 veh/hour/lane, were suffering from degraded operations as 18% of HOV miles during morning peak hour and 32% during evening peak hour had speeds below 45 mph for more than 10% of weekdays, suffered a 20% capacity penalty with maximum flow of 1600 compared to general purpose lanes of 2000 veh/hour/lane and offered small travel time saving compared to general purpose lanes (1.7 min compared to 0.7 min in a 10 mile route). Finally, the authors mention that the system with 1 HOV lane and 3 General purpose (GP) lanes carries the same number of people per hour as a system with four GP lanes and that HOV lanes reduce overall congestion slightly only when the GP lanes are allowed to become congested. They propose that a better managed HOV system might play an important role in California.

Furthermore, Princeton & Cohen (2011) evaluate the impact of a dedicated lane (4.5 km) on the capacity and the level of service of an urban motorway by using aggregated mean speed, flow and occupancy data, gathered from loop detector stations installed throughout the motorway network of the Paris region. For their analysis they used a generalized exponential model to describe the relationship between speed and traffic density: $V = a\, exp\,(-b\, k^{a}\,)$ where V denoted the mean speed k the concentration and a,b were parameters to be decided using nonlinear regression using Gauss-Newton algorithm. By comparing the data before and after the dedicated lane implementation, they concluded that capacity is reduced by 35% and 25% in 3 lane and 4 lane sections respectively and that the level of service is degraded in a significant way upstream of the dedicated lane and very slightly improved downstream. The authors also discussed the effect of enforcement measures on driver compliance. However, the aggregation level of the data used was not discussed in this paper.

Up to date, ACC and CACC have not been evaluated by before and after studies because real world data clearly stating the market penetration rate of the technology do not yet exist for the purpose of evaluating their effectiveness.

3.2.2 Statistical modelling - forecasting

Mathematical or statistical techniques have been applied in order to ex-ante evaluate the impact of the Intelligent Transport Technologies. The difference of this method compared to before and after study approach is that the proposed system is tested before its implementation using statistical modelling. One of the requirements of this approach is the availability of large amount of historical data in order to ensure the high quality of the statistical model developed.

Due to the initial disheartening results of the before and after studies concerning HOV lanes, studies focused on detecting optimal implementation strategies and making recommendations (Dahlgren, 2002; Daganzo and Cassidy, 2008; Schultz, Mineer and Hamblin, 2016). Dahlgren (2002) developed statistical models estimating delay with probabilistic logit models which could estimate the impact of the shift of a GP lane to a HOV or HOT lane. He concluded that except during congestion periods, implementing a general purpose lane is more effective in reducing delay than adding an HOV or HOT lane. An HOV lane would be more effective than HOT or GP lanes only if the proportion of HOVs is high. Furthermore, Menendez and Daganzo, 2007; Daganzo and Cassidy, (2008) used statistical modelling in order to study how HOV lanes affect the performance of adjacent GP lanes and nearby traffic bottlenecks. Their study showed that non-separated HOV facilities do not affect the capacity of GP lanes and that if HOV lanes are implemented properly they do not worsen bottleneck outputs and can increase them under certain conditions. Finally, they suggest three rules which can significantly optimize the impact of HOV lanes.

One of the few studies attempting to evaluate the safety impact of HOV lanes is done by Golob et al. (1990). An extensive methodological analysis of this paper will not be conducted due to the high aggregation level of its data which made the statistical analysis meaningless, something that is recognised by the author.

3.2.3 Traffic Simulation

The majority of studies that aim to evaluate Intelligent Transport Technologies employ traffic simulation due to lack of real-world data. Traffic simulation is the mathematical modelling of transportation systems through the application of computer software to better help plan, design and operate them. This method is going to be analysed further in section 3.3 of this thesis.

Initially, studies evaluate and optimise VSL using traffic simulation (Park and Yadlapati, 2003; Abdel-Aty, Dilmore and Dhindsa, 2006; Lee, Hellinga and Saccomanno, 2006; Allaby, Hellinga and Bullock, 2007; Hellinga and Mandelzys, 2011; Grumert and Tapani, 2012; Li *et al.*, 2014; Yu and Abdel-Aty, 2014; Grumert, Ma and Tapani, 2015; Khondaker and Kattan, 2015). Abdel-Aty et al. (2006) uses data from a section of Interstate 4 in Orlando to evaluate the safety impact of their proposed VSL system by calculating real-time crash likelihood using a statistical model by Abdel-Aty & Pande (2005).

Significant variables in their models included average occupancy, standard deviation of volume downstream of the station of interest, average volume downstream of the station of interest, average volume upstream of the station of interest, standard deviation of speed divided by the average speed at the station of interest, average occupancy upstream of the station of interest, average occupancy downstream of the station of interest and standard deviation of volume downstream of the station of interest. The same study simulated different strategies/scenarios of VSL application based on changing distance for speed limit change, changing speed limits over time and changing the gap. For their simulation they used the simulation software PARAMICS. The results of the simulation showed the optimal VSL implementation scenario which minimized the crash likelihood according to the statistical models developed and included "gradually introducing speed changes in time (5mph every 10 min), abruptly introducing speed changes in space (no gap distance), use upstream reductions in speed and downstream increases in speed and large values changes in speed limit (15 mph)". However, this study did not take into account driver compliance which is critical for intelligent transport systems.

Indeed, Hellinga & Mandelzys (2011) specifically studied the impact of driver compliance on the safety impacts of variable speed limit systems using PARAMICS as well. They tested four different scenarios of low, moderate, high and very high compliance in their simulation. They applied a rule-activated tree-logic which was implemented by Allaby et al. (2007) and is controlled in the simulation environment by using an application programming interface (API).

For their crash risk assessment, the authors of this paper used a crash prediction model originally developed by Lee et al. (2003). The following probabilistic model was decided by compiling loop detector data preceding 299 crashes:

$$\ln(F) = \theta + \Sigma(\lambda_{crashprecursors}) + \Sigma(\lambda_{controlfactors}) + \beta \ln{(EXP)} \tag{3.1}$$

Where F is crash frequency, θ is the constant, $\lambda_{crashprecursors}$ values related to turbulence in traffic stream (coefficient of variation of speed, average density upstream of the tested road section and average difference in speed between upstream and downstream of a specific location), $\lambda_{controlfactors}$ factors to control the effects of road geometry and peak/off peak conditions and EXP exposure in vehicle-kilometres.

The results of the study proved that the VSL impacts are sensitive to the level of speed compliance, as expected. The optimal VSL strategy and set of parameter values are influenced by the level of compliance and as a result, the selection of VSL operating strategy cannot be done without taking the speed limit enforcement into account. Lee et al. (2006) and Allaby et al. (2007) also used the previously mentioned statistical model in combination with PARAMICS. Lee et al.(2006) examined VSL in order to maximize safety benefit and at the same time try to reduce travel times. They concluded that such a scenario exists and that real-time VSL can reduce the overall crash potential by 5-17%. Although, the authors mention that the widespread crash risk model should be expanded to consider a much broader range of traffic flow conditions, road geometry and variable speed limits control strategies.

More recent studies use VISSIM and SUMO simulation software respectively in order to assess the impact of VSL systems combined with Connected Vehicles (Grumert, Ma and Tapani, 2015; Khondaker and Kattan, 2015). The benefit of the examined system compared to the studies in the previous paragraphs is that vehicles were informed for the changed speed limit before they reach the point at which it would be normally displayed by communicating with each other which results in greater safety benefits. Khondaker & Kattan (2015) concluded that safety was improved by 6-11% in their proposed framework. This study also took driver compliance into account and tested two different connected vehicle penetration rates, 50% and 100% with reduced safety benefit in the lower penetration rate scenario. However, the criteria used to determine these rates are not discussed in the paper and there should be more scenarios examined, according to Fagnant & Kockelman (2015). Grumert et al. (2015) indeed, examine more scenarios including 0%, 30%, 70% and 100% penetration rate and obtain results concerning safety, emissions and traffic characteristics which prove that VSL are more beneficial as penetration rate increases.

Traffic simulation has been used in order to assess HOV/HOT lanes also. Gomes et al. (2004) use the microsimulation software VISSIM in order to model an HOV lane in a 15 mile stretch of I-210 in California. Although, the HOV lane is not evaluated as an independent intervention, but instead, the whole network is evaluated. Similarly, according to Owen et al. (2000) the traffic simulation software CORSIM has the capability to simulate all features of an HOV lane. Finally, Stamos et al. (2012), use SATURN simulation software to evaluate the impact of a hypothetical HOV lane implementation in the central business district of Thessaloniki, Greece. Their simulation model was calibrated and validated using average traffic flow data during morning peak hours and their results showed a 129% average speed increase and a 62% decline in the average delay within the area of interest.

Regarding ACC, Bose & Ioannou (2003) used macroscopic traffic simulation in order to evaluate the traffic impact of ACC. For their analysis, they used a linear car following model to model manually driven vehicles and for vehicles equipped with ACC they used a model by Ioannou & Xu (1994) which used a constant time headway policy described by the following equation:

$$S = h_a v + L \tag{3.2}$$

where L is the length of the vehicle, h_a represents the time headway, u the speed and s the inter-vehicle spacing. By comparing density-traffic flow diagrams for 100% and 0% market penetration rates they concluded that in mixed traffic conditions (both manual and ACC equipped vehicles circulate the road network), ACC equipped vehicles lower the average delay experienced in the network, increase traffic flow and density, and increase the speed of propagation of shockwaves without affecting the total travel time. However, this paper does not quantify the results for specific market penetration rates. On the other hand, Kesting et al. (2008) use the Intelligent Driver Model (IDM) by Treiber et al. (2000) in order to simulate the behaviour of an ACC equipped vehicle inside a micro simulation software. The model is shown in the following equation:

$$\dot{u}(s, u, \Delta u) = a\left[1 - \left(\frac{u}{u_o}\right)^4 - \left(\frac{s*(u, \Delta u)}{s}\right)^2\right] \tag{3.3}$$

The model is ruled by adjusting the acceleration of the ACC equipped vehicle in order to keep the required distance from the preceding vehicle. At this point, it must be noted that the same driving model is used for CAV simulation in existing literature. The results of the simulation showed that ACC vehicles improved the traffic stability and road capacity with increased results for higher market penetration rate. As far as the safety impact of ACC is concerned, Kikuchi et al. (2003), introduce Potential Danger Time (PDT) safety measure, which is “the sum of the time periods during which spacing is so short that when a vehicle applies emergency braking it cannot stop without colliding with the vehicle in front”, in order to assess the safety impact of ACC equipped vehicles. They test different scenarios by changing the driver perception-reaction time *T* and conclude that ACC vehicles contribute to the reduction of Potential Danger Time cases and hence the possibility of a rear-end collision.

Furthermore, Li et al. (2016) integrate ACC with a VSL system in order to evaluate the safety impact of ACC equipped vehicles. For their experiment, they use the aforementioned intelligent driver model and the simulation platform of MATLAB. Time to Collision (TTT), Time exposed Time to Collision (TET) and Time Integrated time to collision (TIT) are used as surrogate safety measures to evaluate the risk of rear-end collisions. Four simulation scenarios were tested: No measures applied, VSL only, ACC only finally the combination of both (I2V system). Their results are summarised in the following table.

Table 3.1 Safety effects of 4 scenarios (Li *et al.*, 2016)

Change	**No Control (%)**	**VSL only (%)**	**ACC only (%)**	**I2V system (%)**
TET	0.0	-53.0	-59.0	-71.5
TIT	0.0	-58.6	-65.3	-77.3
TTT	0.0	10.0	-0.4	4.8

Table 3.1 shows the safety impact that the four different tested scenarios had. Greatest safety benefits were achieved when the I2V system was in place.

Over time, studies included inter-vehicle communication in combination with ACC which resulted in CACC evaluation. Similar to ACC, studies focused both on the traffic and safety impact of CACC equipped vehicles. Studies evaluating the safety impact of CACC have used different car following models. Schakel et al. (2010) used an altered/updated Intelligent Driver Model in order to include the connectivity between vehicles. Yu & Shi (2015) and Monteil et al. (2014) on the other hand, developed their own car following models which included terms to represent n plus m vehicles running in a vehicle platoon.

All papers mentioned in the paragraph above concluded in encouraging -yet not comparable due to differences in the driver models used- results regarding traffic. Schakel et al. (2010) and Monteil et al. (2014) observed that CACC can quickly damp shockwaves at lower penetration rates (50%) while Yu & Shi (2015) concluded that their model could improve the stability of traffic flow and reduce the accidental probability.

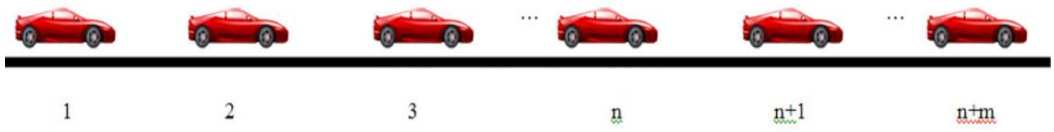


Figure 3.1 A platoon of n+m cars running on a signal lane.

As far as safety of CACC is concerned, Li et al. (2017) use Intelligent Driver Model combined with an ACC model proposed by Kesting et al. (2008) and Time to Collision with the two variations mentioned earlier in this chapter TIT and TET as a surrogate safety measure in order to assess the impact of CACC equipped vehicles on safety. Li et al. (2017) tested a wide range of scenarios including different length of vehicle platoons and different market penetration rates. The simulation results indicated that CACC equipped vehicles dramatically reduced the possibility of a rear-end collision. The sensitivity analysis with platoon length showed that there is no significant change with different platoon lengths, however their analysis included simplifications such as the exclusion of lane changing manoeuvres. In addition, Farah & Koutsopoulos (2014) performed an experiment using test drivers driving an instrumented vehicle with and without the CACC system in order to estimate their car following model. Their simulation results showed that CACC harmonized the driving behaviour of drivers and reduced the range of acceleration and deceleration differences between them.

Additionally, Arem et al. (2005) and Zhao & Sun (2013) used traffic simulation software MIXIC and VISSIM respectively in order to assess CACC. Similar to the results mentioned on other studies in the paragraphs above, Arem et al. (2005) and Zhao & Sun (2013) conclude that the traffic capacity benefit increases as market penetration of CACC vehicles increases. On the other hand, the length of the platoon did not affect the benefit. However, these two studies included major assumptions such as that vehicles equipped with CACC would not perform lateral movements in a 2-lane network while simulating.

Last but not least, Shladover et al. (2012) uses the traffic microsimulation software Aimsun in order to identify the impacts of CACC on Freeway Traffic Flow. In his simulation, the author modelled four different types of vehicles: ACC equipped, CACC equipped, those equipped with communication device making them able to transmit the data of the ego-vehicle such as speed position and acceleration and vehicles not equipped with any Intelligent Transport Technology. The author chose different desired time gaps for Manually Driven, ACC and CACC equipped vehicles of 1,48-1,8 sec, 2.2-1.1 sec, 1.1-0,6 sec accordingly. Initially, ACC vehicles entered the simulation traffic stream which did not result in remarkable difference in capacity due to the fact that the time gap between ACC vehicles and regular vehicles was not significantly different. However, when CACC vehicles were tested in the simulation, road capacity increased incrementally with the market penetration rate as presented in Figure 3.2. Purple colour in the figure represents the market penetration rate of

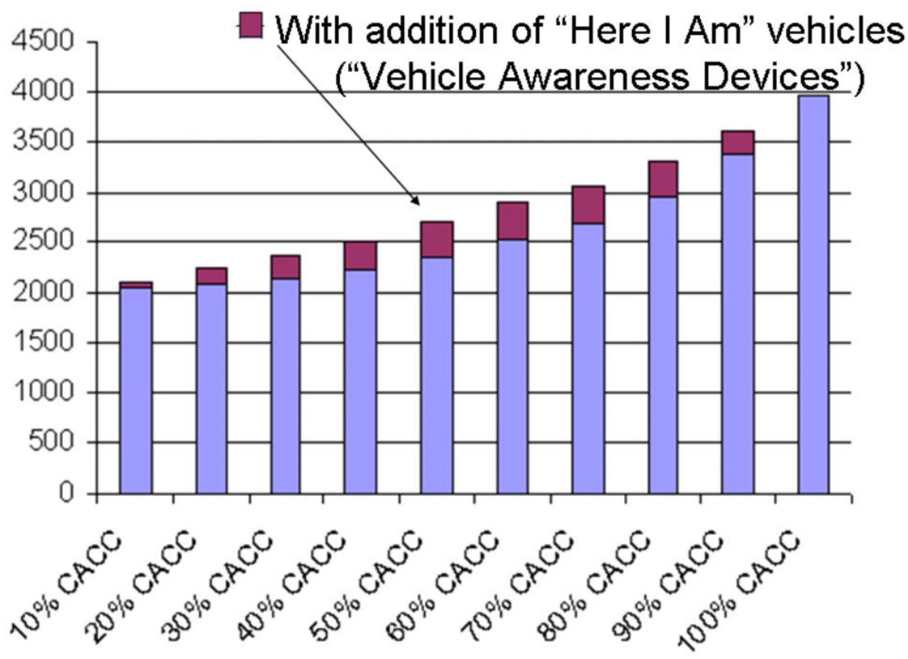


Figure 3.2 Highway Lane Capacity as a function of changes in market penetration (source: Shladover et al. (2012))

vehicles equipped with communication devices only. It should be noted that vehicles equipped with CACC following a non-CACC equipped vehicle transformed into ACC equipped vehicle. Finally, different combinations of CACC and ACC equipped vehicles were tested with the results presented in Table 3.2. It is observed that as CACC vehicles market penetration rate increases, lane capacity increases significantly.

Table 3.2 Lane Capacity effects of ACC and CACC Driven Vehicles. source:(Shladover, Su and Lu, 2012)

	Percentage of CACC Vehicles								
Percentage of ACC	10%	20%	30%	40%	50%	60%	70%	80%	90%
10%	2065	2090	2170	2265	2389	2458	2662	2963	3389
20%	2065	2110	2179	2265	2378	2456	2671	2977	0
30%	2077	2127	2179	2269	2384	2487	2710	0	0
40%	2088	2128	2192	2273	2314	2522	0	0	0
50%	2095	2133	2188	2230	2365	0	0	0	0
60%	2101	2138	2136	2231	0	0	0	0	0
70%	2110	2084	2155	0	0	0	0	0	0
80%	2087	2101	0	0	0	0	0	0	0
90%	2068	0	0	0	0	0	0	0	0

3.2.4 Summary

This methodological review chapter aimed to identify the main methods used for the evaluation of Intelligent Transport Technologies to derive an initial indication for the appropriate method to evaluate CAVs.

The methods included in this chapter have obvious advantages and drawbacks. Before and after empirical studies can provide reliable results as they are being based on real world data before and after the implementation of the technology itself. However, the nature of this method is its main drawback for the case of CAVs. Despite the numerous CAV trials around the globe, there are still no available real world CAV data in order for this method to be applicable. A similar conclusion can be drawn for the statistical modelling/forecasting method. In order for this method to be applied, there is a need for a big amount of historical data. Since historical real-world CAV data are not available, this method might not be applicable for the evaluation of CAVs. However, forecasting techniques might be useful to be applied in the future in order to forecast the impact of CAVs using simulated data.

The fact that real-world data are not available for CAVs indicate that the most appropriate method that can be used for CAV evaluation is traffic simulation. However, this chapter made obvious that studies (CACC studies mainly) employing traffic simulation include assumptions which are very detailed and justified, yet their realism is completely unknown. These assumptions were related to fundamental elements of the research:

a) The type of traffic simulation used (macro vs micro)
b) Network layouts of the simulation frameworks,
c) ACC and CACC parameters such as time headway
d) Underlying assumptions; fundamental driver models employed both for the human drivers (different simulation software) and the ACC and CACC models (IDM vs custom made models).

Their results are based almost solely on the assumptions of the traffic simulation and the comparison of the results of these studies is almost impossible. However, with the lack of real-world CAV data and the amount of uncertainty around them assumptions are inevitable. For the choice of assumptions of CAV modelling one should look into relevant existing CAV literature. Hence, the next section will focus on attempts to simulate CAVs so far in the literature to derive the most reasonable assumptions.

3.3 Review of Methodological Approaches in Connected and Autonomous Vehicle Simulation

3.3.1 Review of simulation frameworks for CAV simulation

Are CAVs safe enough now? Will CAVs be safe enough when they start occupying the road network? The answer to these questions is critical. One way to answer these questions would be to test drive CAVs in real traffic, evaluate their performance and statistically compare "before CAVs and after CAVs" periods. However, this would be incredibly challenging according to Kalra & Paddock (2016), as, CAVs need to be driven hundreds of millions of miles or in some cases hundreds of billions of miles to demonstrate their reliable behaviour in critical, life-threatening situations. Even though Original Equipment Manufacturers (OEMs) such as Waymo, Tesla, Ford, Volkswagen and BWM (to name a few) have been focusing in real world CAV trials, this amount of such exposure data is not available yet to them. Consequently, the research community also does not have access to CAV data. That is why the biggest part of the literature reviewed in this section has either speculated on the impacts of CAVs using historical data or used innovative approaches such as simulation to evaluate CAVs. Therefore, this part of the literature review is divided into two subsections:

a) Studies employing historical data
b) Studies using simulation

It is worthwhile to point out that only a few studies have evaluated the safety impact of CAVs. Nonetheless, studies focusing on traffic or the environment are included in this section and are methodologically reviewed. Also, where appropriate, the possible use of the methods employed in those studies for safety evaluation purposes, is discussed. It must be emphasized that studies mentioning or implying both vehicle automation and connectivity are considered in this section, because a number of previous studies exist that have evaluated the safety impact of automated vehicle technologies highly related to CAVs such as ACC (Kikuchi, Uno and Tanaka, 2003; Li *et al.*, 2016) and CACC. (Farah and Koutsopoulos, 2014; Shladover, Station and Lu, 2015; Li *et al.*, 2017c). Although these studies provided a stepping stone for future CAV research by using sophisticated CACC algorithms and Intelligent Driver Model, their major limitation is that they did not consider vehicle automation in the sense of simulating the behaviour of sensors and did not include a vehicle lateral control algorithm.

a) Studies employing historical data

Some papers attempt to predict the potential safety impact of CAVs (Hayes 2011; Silberg et al. 2012; Fagnant & Kockelman 2015) using historical accident data and performing a meta-analysis.

By processing this historical crash data and categorising them by contributing factors, these papers claim that since the human factor will not exist in the autonomous era, the corresponding percentage of accidents will be eliminated. In this manner, it is suggested that an up to 90% reduction in crash rates (subject to CAV market penetration rate) can be achieved with the introduction of CAVs (Fagnant & Kockelman 2015)

Another approach in this category of studies aims to compare CAV implementation to the implementation of automated technologies in aviation or rail. It is suggested that, during the fully autonomous era, road crash rates could be as rare as those of aviation and rail, ultimately reaching 1% of the current figures (Hayes, 2011). Even though the use of such a parallelism can be useful and admittedly the introduction and the process of implementation of technologies such as Airborne Collision Avoidance System has certain similarities with the introduction of CAVs, it contains assumptions that can affect the reliability of the research.

In summary, although these methods have provided a sense of the magnitude of the safety benefits, they are based on a series of crude assumptions. For example, this approach does not consider CAV interaction with other road users such as human drivers, pedestrians and signalling which is going to be critical during the transition period. These assumptions may affect the capability of this approach to produce reliable outcomes.

b) Studies applying CAV traffic simulation

The lack of CAVs real-world data has diverted a part of the research community from traditional safety evaluation methods to simulation-based approaches to evaluate their impacts. Traffic simulation is the mathematical modelling of transportation systems through the application of computer software to better help plan, design and operate transportation systems. It is a flexible tool that has proven to be valuable due to its ability to ex-ante evaluate transportation technologies. It is perhaps the only method that can accurately address some of the unprecedented challenges arising by the introduction of CAVs in the existing transport system, namely, the interaction of human-driven and CAVs, the different levels of automation or the transformation of the existing road network to incorporate them.

However, simulation has received reasonable criticism over time about its ability to produce trustworthy results especially in the area of road safety (Tarko, 2005). A well calibrated and validated simulation model and an excellent awareness of the capabilities and functionalities of the technology under review are key prerequisites of every simulation study. Given the uncertainty regarding the future developments of CAVs (for example, the interactions between human-driven vehicles and Connected and Automated Vehicles during the transition era is highly unknown) and the lack of data regarding Connected and Automated Vehicle Driving behaviour, the aforementioned prerequisites are usually not satisfied. Consequently, the body of the literature employing simulation relies on justified and valid assumptions which in most cases are the key for the reliability of the results.

A paradox when trying to simulate CAVs is that vehicles inside a simulation environment are not programmed to collide with each other since they are already aware of their surroundings. Therefore, arguably, vehicles in a traffic micro-simulation have already the knowledge that autonomous vehicles have since they have all the available information they need. However, what makes an autonomous vehicle different from a non-automated, is its ability to translate the input from its sensors into real world actions. This ability of the CAV should be the factor to be simulated and tested in a simulation study.

Simulating CAVs is a multifaceted task. Each CAV is a complex entity consisting of multiple subsystems that need to be simulated in order to address the challenges arising from the different types of road network layout. The way that these subsystems are simulated (i.e. the tools and software used and the underlying assumptions) and the achieved level of detail are the criteria that lead to the categorisation of existing studies into two major groups:

- Studies using an architecture including traffic sub-microsimulation
- Studies using traffic microsimulation and an external component

3.3.1.1 Studies using an architecture including traffic sub-microsimulation frameworks

The first approach included studies that used custom-built simulation frameworks (Queck *et al.*, 2008; Figueiredo *et al.*, 2009; Noort, Arem and Park, 2010; O'Hara *et al.*, 2012; Pereira and Rossetti, 2012) These studies aimed to achieve detailed CAV simulation by creating an integrated multi-level simulation platform which in most cases included traffic, sensor (sub-micro) and network simulators.

This type of frameworks included usually a sub-micro simulation software which could simulate all the components of the vehicle accurately. This means for instance, that the sensors of the vehicle are simulated individually and their specifications such as the scanning frequency, or the number of scanning beams can be directly set. Moreover, they provide physical models for the car itself, such as the tyres, suspension and engine. The control algorithms for the “actors” of the simulation scenario (i.e. cars, traffic signals etc) are usually programmed in an external software such as Matlab/Simulink which communicates with the sub-micro simulation tool every simulation step via a Transmissions Communication Protocol (TCP/IP), exchanging data. Some studies in this category have attempted to create a more integrated simulation framework by combining these sub-micro simulators with communications simulators and traffic microsimulation tools which can provide a more sophisticated surrounding traffic environment.

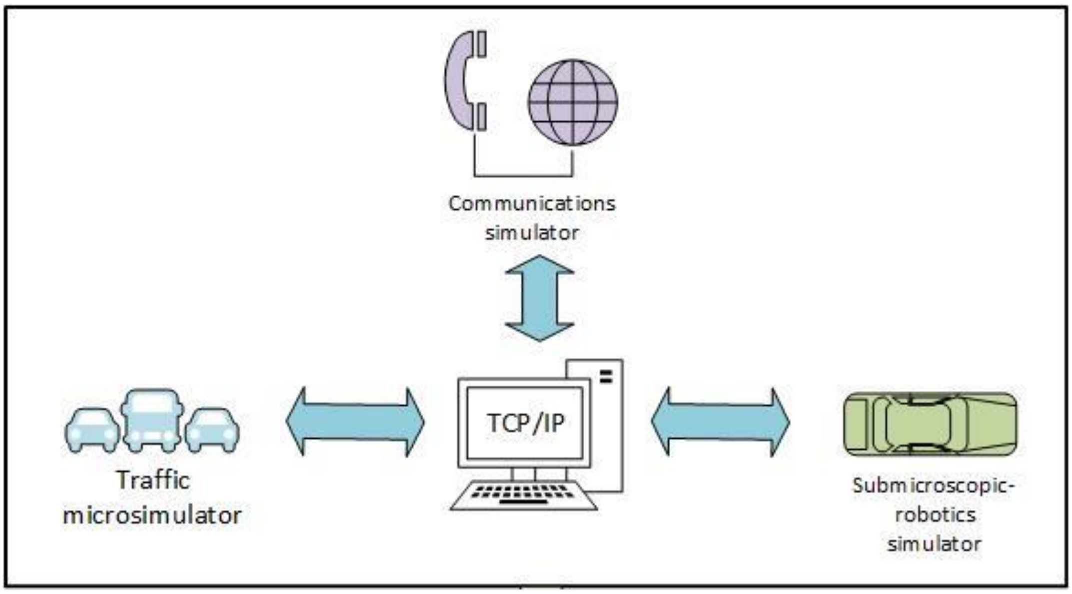


Figure 3.3 Submicroscopic simulation framework

The aforementioned simulators could cooperate on-line using an external platform, in order to form an integrated simulation architecture (see Figure 3.3). A variety of different software have been used in the literature. Pereira (2011), for instance, after critically evaluating all available traffic simulation software, used SUMO (Simulation of Urban Mobility) an open source traffic simulation software, in order to simulate the road network and traffic stream, while O’Hara et al. (2012) used PTV’s traffic simulation software VISSIM and finally Figueiredo et al. (2009) used MAS-T^{2}er Lab’s microscopic traffic simulator. An in-depth comparison of the available traffic simulation software and their capabilities in simulating autonomous vehicles are discussed in section 3.3.2. As far as sub-microscopic simulators and network simulators are concerned, Pereira (2011) used USARSim (Unified System for

Automation and Robot Simulation) robotics simulator and a built-in feature of SUMO in order to simulate the communication element of the simulation framework, while O'Hara et al. (2012) use Microsoft Robotics Developer Studio (MRDS) and OPNET for robotics and communication simulation respectively. On the contrary, Figueiredo et al. (2009) did not employ any robotics or communication simulator.

All of these studies have provided high detailed CAV simulation. However, the developed frameworks had high computational needs that led to several downsides. Firstly, they were very complex. This consequently affected the size of the networks designed for the studies (compared to the size of the networks of the alternative approach) and this fact did not permit the collection of a sufficient amount of data that could be statistically analysed in order to calculate CAV impacts. Finally, due to the significant differences in the underlying algorithms their results cannot be directly compared.

From the above, it is concluded, that such a framework is highly capable of evaluating the safety impact of CAVs at small scale. For example, an experiment that would include a small number of vehicles could be easily simulated in such frameworks and by implementing several highly detailed CAV sensing, planning and control algorithms, the small-scale safety impact of these vehicles could be evaluated. However, this is beyond the scope of this PhD thesis. The aim of this thesis is to evaluate the safety impact of CAVs on motorways -a large scale network. This type of framework cannot easily evaluate the network-level safety impact of CAVs because of the size limitations of its experiment, hence it will not be considered for this thesis.

3.3.1.2 Studies using traffic microsimulation and their external component

The second group of studies aims to address the aforementioned shortcomings regarding experiment size and computational needs by using a simpler simulation framework architecture. (e.g. Li et al., 2013; Jeong, Oh and Lee, 2017; Rahman and Abdel-Aty, 2018; Stanek et al., 2018). In most cases, a commercially available traffic microsimulation tool (such as AIMSUN, VISSIM, Paramics or SUMO) is used along with its external component such as a Component Object Model (COM) or an

Application Programming Interface (API). The microsimulation tool is responsible to represent the infrastructure and create the traffic in the predefined road layout while the external component aims to simulate the CATS functionalities. These functionalities are programmed in a programming language such as Matlab, Python or C++. The microsimulation tool communicates with the external component every simulation step exchanging data such as vehicle positions and kinematic characteristics of the traffic in the simulation experiment (see Figure 3.4). Based on this data, the external component calculates the actions of the CATS at each simulation step. Examples of such external components is the External Driver Model used in this thesis and the Aimsun Next API provided by the software Aimsun.

The architecture described above is simpler than the one stated in the first group, however, inevitably, it leads to the following disadvantages: (i) the level of detail achieved is low, and (ii) most importantly, the number of subsystems and functionalities of a CAV that can be simulated are limited and can only be indirectly simulated. For instance, for the sensing subsystem, only some characteristics such as the sensor range can be effectively programmed, ultimately leading to more and serious assumptions (e.g. Rahman *et al.*, 2019b). Additionally, simplifications are made in order to simulate Connected and Automated Driving. For instance, in most simulation studies, it is typically speculated that Connected and Automated Vehicles will be able to keep a smaller time headway than human driven vehicles, however, the exact mathematical formulation of the longitudinal movement is still unknown.

Justifying the assumptions and simplifications might be crucial to prove the trustworthiness of the platform. On the other hand, the computational needs of this method are reasonable, and the size of the experiment is not a limitation. As a result, the simulation outputs could be more easily interpreted, transferred and generalised.

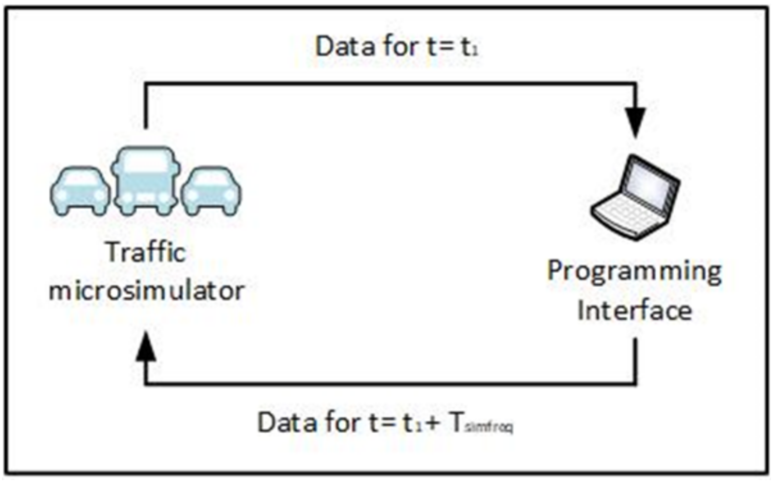


Figure 3.4 Traffic microsimulation CAV framework Approach

Table 3.3 Presents a summary of existing microsimulation based studies for CAVs following this approach (adapted from Rahman *et al.*, 2019a). It must be emphasized that all studies mentioned in this table include differences in their definitions of CAVs' hence a different term for the investigated technology is mentioned in them (C onnected Vehicle (CV) – Autonomous/Automated Vehicle (AV) Connected and Autonomous Vehicle (CAV)). However, in principle, the underlying research is similar between the studies and therefore, all of them are included in the table. The most methodologically relevant studies from Table 3.3 are going to be further analysed below.

Table 3.3 Existing simulation-based studies for CAVs

Paper	**Car following model**	**Software**	**Technology**	**Study area**	**Impact area**
(Talebpour and Hani S Mahmassani, 2016)	IDM	Custom	CAV	Freeway	Traffic
(Rahman *et al.*, 2019a)	IDM	VISSIM	Connected Vehicle (CV)	Freeway	Safety
(Guériau *et al.*, 2016)	IDM	MOVSIM	CV	Freeway	Traffic and **Safety**
(Wan, Vahidi and Luckow, 2016)	Paramics Default	PARAMICS	CV	Arterial	Traffic and fuel

(Genders and Razavi, 2015)	Modified Driving Behaviour	PARAMICS	CV	Arterial	Safety
(Wu, Li and Zhang, 2015)	VISSIM default	VISSIM	CV	Arterial	Traffic
(Ilgin Guler, Menendez and Meier, 2014)	N/A	Matlab	CV	Arterial	Traffic
(Jin *et al.*, 2014)	Optimal driving behaviour	SUMO	CV	Arterial	Traffic and fuel
(Jin *et al.*, 2013)	SUMO default	SUMO	CV	Arterial	Traffic and fuel
(Lee and Park, 2012)	VISSIM default	VISSIM	CV	Arterial	Traffic operations
(Fernandes and Nunes, 2010)	Gipps model-IDM	SUMO	Automated Vehicle (AV)	Freeway	Traffic
(Qian *et al.*, 2014)	SUMO default	SUMO	CAV	Arterial	Traffic
(Stanek *et al.*, 2018)	VISSIM default	VISSIM	CAV	Freeway	Traffic
ATKINS, 2016b	VISSIM default	VISSIM	CAV	Freeway and Urban	Traffic
Li *et al.*, 2013	VISSIM default	VISSIM	CAV	Intersection	Traffic and **Safety**

There is a series of studies that used VISSIM to simulate CAVs (Park *et al.*, 2012; Li *et al.*, 2013; ATKINS, 2016a; Jeong, Oh and Lee, 2017; Stanek *et al.*, 2018; Rahman *et al.*, 2019b) . Li et al. (2013) used the External Driver Model API of VISSIM to model autonomous intersection control. They used a reservation-based intersection control system which operated autonomously. The performance of the proposed External Driver Model Algorithm was evaluated for traffic and safety purposes. The safety performance of the autonomous intersection control proved to be highly effective producing only one traffic conflict in 1,800 seconds of simulation. However, the method applied in this paper is designed specifically for intersections and is not transferrable to the network or corridor level.

ATKINS (2016) and Stanek *et al.*, (2018) used VISSIM to evaluate the impact of CAVs in urban and motorway networks with respect to the efficiency of traffic flow. Several times of the day (peak-off peak) were tested in different road network scenarios (urban – SRM motorway). Their report focused on the alteration of the default driver model parameters of VISSIM to simulate CAVS. Despite using a wide range of CAV market penetration rates, time headways between vehicles to represent different automation levels and CAV- orientated parameters, CAV decisions were ultimately made through the default driver model of VISSIM which is calibrated for human driving behaviour. This alteration cannot be directly connected to or imply full vehicle automation and connectivity. Therefore, the number and importance of assumptions of this study could affect its ability to produce reliable outcomes. A possible use of this method for safety evaluation could show inaccurately increased simulated traffic conflicts due to the stricter headway safety parameters of VISSIM.

Finally, more relevant studies to this PhD were conducted by Jeong et al. (2017) and Rahman *et al.*, (2019a). Rahman *et al.*, (2019a) used VISSIM along with its extension Application Programming Interface. In order to simulated CAVs they used the Intelligent Driver Model developed by (Kesting, Treiber and Helbing, 2010) which has been used widely in the literature to simulate CAV driving behaviour. However, there is no evidence in the literature proving that this is an appropriate model for CAV modelling. The high-level result of their model was that CAVs were able to drive with shorter headways leading to the formulation of vehicle platoons. Besides the CAV driver model, one additional drawback of this study and most of the studies included in Table 3.3 is the fact that fundamental inherent challenges arising by the sensing subsystem (such as sensor accuracy) and planning subsystem such as real-time routing and platoon formulation logic (Mouhagir *et al.*, 2017).

There are a few attempts to cover these drawbacks from existing literature. However, most of the attempts do not manage to assess their method in an integrated experiment. For example Zhou *et al.*, (2017) attempted to include sensor errors in a custom Matlab simulation environment. Using a rolling horizon stochastic optimal control strategy, they investigated the impact of inaccuracies in sensor measurements and system dynamics on driving comfort and control efficiency. Their results showed that their proposed strategy could generate smoother vehicle control. However, the experiment in which the strategy was tested could not reflect the impact of inaccuracies in sensor measurements on the safety of a validated motorway network.

Additionally, previous studies have expressed concerns about platoons compromising road safety and traffic stability if the platoon size is too long, especially if it is running in the outermost lane of a motorway. Jiang, Li and Shamo, (2006), attempted to identify the optimal platoon size and intervehicle spacing, in order to develop a platoon-based traffic signal timing algorithm that would reduce traffic delays. Similarly, Varaiya, (1993) underlines that platoon size is correlated with intra-platoon spacing and identifies 60 meters to be a sufficient gap between two consecutive vehicle platoons to allow vehicle manoeuvres between platoons. Nevertheless, they do not recommend an optimal platoon size that maximizes safety benefits. Finally, Zhao and Sun, (2013) investigate the impact of platoon size and CAV market penetration rate on traffic capacity. They conclude that platoon size alone has minimal impact on capacity. Yet, they state that when a large platoon (8 to 10 vehicles) performs a lateral manoeuvre, a disruption in traffic flow is inevitable. This implies that a well-planned CAV size must be defined so as to minimize potential disruption in traffic flow and as a consequence the occurrence of safety-related events.

Based on the above, the following conclusion can be drawn. Existing literature has taken valuable steps to evaluate CAVs. However, most of the studies have a narrow scope and focus on specific elements of CAV driving. Hence a first research gap is identified. There is a need to develop an integrated CAV simulation evaluation framework that -with justified assumptions- will incorporate and address as many inherent CAV challenges arising from the nature of the subsystems of CAVs as possible in an integrated framework that will be able to evaluate the safety impact of CAVs.

3.3.2 Review of existing simulation tools

Literature review so far showed that traffic simulation has been used extensively to assess impacts of Intelligent Transport Technologies and CAVs. According to the desired level of detail traffic simulation can be divided into four categories: Macroscopic, Mesoscopic, Microscopic and Sub-microscopic.

Macroscopic simulation or macrosimulation is based on mathematical equations simulating the flow of vehicles in a road network, an approach which originates from fluid dynamics. This type of traffic simulation aims to model vehicle dynamics collectively in terms of spatial vehicle density and average velocity as a function of road location and time (Helbing *et al.*, 2002). In practice, it has the capability to simulate the traffic dynamics in all lanes using single lane models considering a certain probability of overtaking, ultimately reducing computational needs. However, as of today, it is still unknown if traffic macrosimulation can incorporate CAVs in terms of driving models or intelligent transport technologies. In macroscopic simulation, the traffic flow is distributed in the road network based on the Origin-Destination matrix and an equilibrium state is reached through multiple steps of calibration, similar to Nash's equilibrium game theory in which no simulated car can achieve a better travel time by altering its trajectory.

Mesoscopic traffic simulation is the middle ground between microscopic and macroscopic traffic simulation. Mesoscopic simulation usually can simulate transport elements (such as an extensive part of a large road network) within which, elements (passenger vehicles – public transport – roads etc.) are assumed homogeneous. One of its advantages is the simulation speed and the fact that it provides more detail than macroscopic simulation. However, compared to microscopic models, mesoscopic models have a lower level of detail. For example, mesoscopic models usually use simplified car-following models and can only gather aggregated simulated vehicle data compared to individual vehicle data.

Microscopic traffic simulation or traffic microsimulation aims to simulate the behaviour of individual vehicles within a predefined road network and is used to predict the likely impact of changes in traffic patterns resulting from changes to traffic flow or from changes to the physical environment. Microsimulation consists of sets of mathematical models such as car following models, lane-changing models, and signalling models simulating individual vehicles behaviour. Recently, microsimulation has been used extensively due to its ability to include external tools such as a Component Object Model (COM) or an Application Programming Interface (API) in order to simulate externally custom technologies.

The final category of traffic simulation is sub-microscopic simulation. It has the aim to simulate all the components of a vehicle accurately. For example, sensors and internal components (engine, steering wheel etc) of the vehicle are simulated individually and their specifications can be directly set. The control algorithms for the "actors" of the submicroscopic simulation scenarios are usually programmed by the user usually in an external software such as Matlab/Simulink which communicates with the sub-micro simulation tool every simulation step via a Transmissions Communication Protocol (TCP/IP), exchanging data.

Finally, hybrid traffic simulation is a flexible type of simulation and is the combination of mesoscopic and microscopic simulations allowing the user to model large areas while zooming in on specified areas that require a microsimulation level of detail. It must be noted that it has not been used widely in the literature.

In order to select the appropriate tool for the development of the simulation framework of this PhD thesis, a comparative description of the most available widespread traffic micro-simulation software is performed below: AIMSUN, MITSIM, PARAMICS, VISSIM, SUMO, MAS-T2er Lab and PreScan and CARLA (Boxill and Yu, 2000; Kokkinogenis *et al.,* 2011; Pereira, 2011).

1. **AIMSUN**. was developed by J. Barcelo and J.L.Ferrer of the Polytechnic university of Catalunya in Barcelona, and is capable of performing macro- and micro-simulation. Its micro-simulation includes several driver behaviour models (car following, lane changing, gap acceptable). It provides detailed statistical outputs with flow, speed, travel time and delay data. It can simulate in detail all different elements of a road network such as vehicles, detectors and traffic lights. It also can simulate incidents and conflicting manoeuvers. Reed (2015) has recently developed a new AIMSUN package which allows the simulation of inter-vehicle communication in the simulation environment.

   The car following model of AIMSUN is a car following model developed by Gipps (Gipps, 1981) in which the maximum speed to which a vehicle (n) can accelerate during a time period (t, t+T) according to its surroundings is given by the equation:

$$V_a(n,t+T) = V(n,t) + 2.5a(n)T\left(1 - \frac{V(n,t)}{V^*(n)}\right)\sqrt{0.025 + \frac{V(n,t)}{V^*(n)}} \quad (3.4)$$

Where Va(n,t) is the speed of vehicle n at time t, V*(n) is the desired speed of the vehicle (n) for current section, a(n) is the maximum acceleration for vehicle n, and T is the reaction time which corresponds with the simulation time step. Additionally, the maximum speed of the same vehicle is rules by its own characteristics and the limitations imposed by the presence of the lead vehicle (vehicle n-1). Hence the speed of the ego vehicle is ruled by the following equation as well:

$$V_b(n,t+T) = d(n)T + \sqrt{d(n)^2T^2 - d(n)\left[2\{x(n-1,t) - s(n-1) - x(n,t)\} - V(n,t)T - \frac{V(n-1,t)^2}{d'(n-1)}\right]} \quad (3.5)$$

Where d(n) (< 0) is the maximum deceleration desired by vehicle n;

• x(n,t) is position of vehicle n at time t;

• x(n-1,t) is position of preceding vehicle (n-1) at time t;

• s(n-1) is the effective length of vehicle (n-1), computed as length of vehicle (n-1) plus the minimum clearance of vehicle (n). This minimum clearance is the distance, in metres, that a vehicle keeps between itself and the preceding vehicle when stopped;

• d'(n-1) is an estimation of vehicle (n-1) desired deceleration.

2. **MITSIM** was developed at the Massachusetts Institute of Technology for modelling traffic flows purposes. Similar to AIMSUN, MITSIM represents individual vehicles in the simulation environment by using car following, lane changing and traffic signal response models. MITSIM can provide real-time sensor data that imitate the surveillance capacities of the traffic management systems in an ITS environment. There has been however no attempt so far making it able to simulate vehicle connectivity or autonomy.
3. **PARAMICS** is a software developed at the Edinburgh Paralled Computing Center in Scotland. It includes a sophisticated car-following and lane changing

model for roads up to 32 lanes in width. Paramics gives every driver/car couple specific characteristics which make it capable of assessing environmental impacts as well as traffic impacts of interventions. This gives the user the ability to make measurements of the simulation as it progresses. Finally, Paramics can model the interaction between drivers and ITS. Again, no work has been found in making it suitable for modelling connected and autonomous vehicles.

4. **VISSIM** is a microscopic traffic simulation software developed by PTV GROUP which is time step and behaviour based. It can model urban traffic and public transport. Through VISSIM, the user can program different traffic flow compositions, traffic signals, variable message signs etc, making it a useful tool to test different scenarios. Its results include detailed travel, delay, queue length, signal timing information and speed data. VISSIM has also the capability to simulate vehicle connectivity and ADAS by using its feature - External Driver model. The main car following model in VISSIM is the Wiedemann driver model which is going to be analysed in chapter 4.
5. **SUMO** is a highly portable microscopic simulation software developed by the Institute of Transportation Systems at the German Aerospace Center and is able to simulate large road networks. It is widely used by academia and research community mostly due to the fact that it is open-source and highly editable. SUMO can be connected with external applications through a Transmition Control Protocol (TCP)-based client-server architecture which makes it a suitable tool to simulate autonomous vehicles with the integration of robotics and communication simulators such as NS3 or OPNET.
6. **Mas-T2er Lab** is a simulation tool developed by MAS-T2er Lab Group and is an integrated multi-agent system that allows the assessment of ITS through external agents.
7. **PreScan** is an off-line simulation tool which allows the testing of many different traffic scenarios in a virtual environment. PreScan is the only commercially available software capable of simulating sensor processing and control algorithms within its simulation environment without including any external agent. Although it has high computational needs and cannot simulate large traffic flows and road networks.

8. **CARLA** is a software that has been developed from the ground up to support development, training and validation of autonomous driving systems. In addition to open source code, CARLA provides open digital assets like urban road networks, buildings and vehicles that can be used freely by the user. This software supports sensor configurations, environmental conditions, full control of all static and dynamic actors of the simulation and finally map generation.

In this section, the commercially available traffic micro-simulation software will be compared using the following criteria which were originally employed by Pereira (2011) :

- **Extensibility**: The capability of the software to cooperate with other simulation tools and the possibility to reach core of the simulation.
- **Type of License**: Simulation software can be either open-source or closed source. Open source simulation software are usually inferior in features but they are more adaptable than closed source simulators due to community support.
- **External Agent Support**: The ability of the software to include an external agent able to control driver behaviour.
- **V2X communication**: The ability of the software to simulate communication between vehicles and between vehicles and infrastructure
- **Acceptance**: Whether the software is widely accepted and used by the scientific community.
- **Parallelism/Core distribution**: The ability of the software to distribute the simulation computing to different CPU cores or more than one computers.

Table 3.4 shows which of the aforementioned traffic simulation software meet the criteria.

Table 3.4 Feature Comparison of microscopic traffic simulators for agent-based autonomous vehicle simulation source: (Pereira, 2011)

Simulator	Extensi-bility	Type of License	External Agent Support	V2X	Acceptance	Parallelism
VISSIM	Yes	Commercial	No	No	High	Yes
PARAMICS	Yes	Commercial	No	No	High	Yes
AIMSUN	Yes	Commercial	Yes	No	High	Yes
MITSIM	Yes	Both	No	No	Low	Yes
SUMO	Yes	Open-Source	Yes	No	High	Yes
MAS-T2er Lab	Yes	Free	Yes	No	Low	Yes
PreScan	Yes	Commercial	Yes	Yes	Low	Yes
CARLA	Yes	Open-Source	Yes	Yes	Low	Yes

During this PhD project, the simulation software AIMSUN, VISSIM, PreScan, SUMO and CARLA were evaluated for the purpose of the project. The commercially free for researchers traffic microsimulation software VISSIM 9.0 along with its extension External Driver Model was decided to be used because it is widely accepted from the research community (Wu, Sun and Yang, 2005; Huang *et al.*, 2013; Yu and Abdel-Aty, 2014; Shahdah, Saccomanno and Persaud, 2015; Katrakazas, Quddus and Chen, 2018; Rahman *et al.*, 2019c), fulfilled the criteria analysed in this section and due to the fact that it had all the necessary functionalities to simulate CAVs.

3.4 Safety Analysis Using Traffic Microsimulation

As mentioned in section 3.3, traffic microsimulation is ruled by a set of mathematical equations which define the driving behaviour of individual vehicles inside the software. However, in most cases these equations contain safety parameters which do not allow vehicles to create accidents which are according to safety related literature the main safety performance indicator. This statement is a paradox and can affect the reliability of the use of simulation for safety evaluation purposes. Indeed, for this reason, traffic microsimulation has received criticism for its incapability to evaluate road safety (Tarko, 2005; Saunier, Sayed and Lim, 2007).

On the other hand, there are a plethora of microsimulation studies that support the use of the method for safety evaluation, if and only if the simulation model is well calibrated and validated using safety indicators (Fan *et al.*, 2013; Huang *et al.*, 2013; Essa and Sayed, 2015; Shahdah, Saccomanno and Persaud, 2015; Rahman *et al.*, 2019b).

In the absence of accidents, most of the aforementioned simulation based literature has relied on alternative safety indicators that instead of accidents can detect safety incidents. Heinrich, (1941), developed the renowned Heinrich's pyramid in which he implied that there is a clear functional relationship between the number of safety incidents and accidents. This concept has been adapted in 1987 by Hydén, (1987). Hyden introduced the pyramid of Figure 3.5 which describes the evolution of

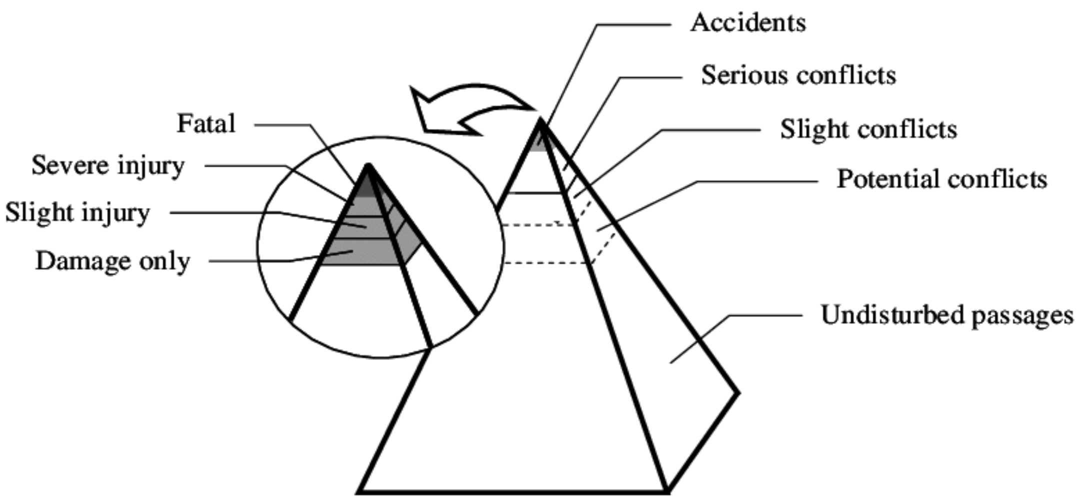


Figure 3.5 Hyden's safety pyramid

vehicle interactions from undisturbed passages to accidents. The middle ground between accidents and undisturbed-safe passages is defined as conflicts. Despite the decades of conceptual development and widespread application, according to a recent study, there are still some disputes on what a traffic conflict is (Zheng, Ismail and Meng, 2014). There is a consensus that the nature of a traffic conflict is twofold. Initially, it is defined by a surrogate safety measure which indicates a spatiotemporal danger (two vehicles are too close either in space or in time) and secondly, an evasive manoeuvre is taking place in order to avoid a potential accident (Hydén, 1987; Zheng, Ismail and Meng, 2014). Hence, a definition that can be given to traffic conflict is an event involving two or more moving vehicles approaching each other in a traffic flow stream in a manner that a traffic accident would occur unless at least one of the involved parties performs an evasive manoeuvre.

Based on this definition a large part of the simulation-based literature has used traffic conflicts as a safety indicator (Federal Highway Administration, 2003; Li *et al.*, 2013; Zhao and Sun, 2013; Katrakazas, Quddus and Chen, 2018; Rahman and Abdel-Aty, 2018). A functional relationship between traffic conflicts and accidents can be found in Gettman *et al.*, (2008) and is presented below.

$$\frac{Crashes}{Year} = 0.119 * \left(\frac{Conflicts}{Hour}\right)^{1.419} \qquad \textbf{(3.6)}$$

Nevertheless, as mentioned in the previous paragraph, the two conditions - spatiotemporal proximity and evasive manoeuvre - need to be quantitatively defined in order to clearly define a conflict within a traffic simulation software. Hence, the concept of surrogate safety measures is introduced. Surrogate safety measures are the measurements that are used to describe the relationship between two road users in a traffic event for the purpose of quantifying the accident probability and/or the potential accident severity in a meaningful way (De Ceunynck, 2017). There is a plethora of surrogate safety measures employed in traffic simulation studies in order to evaluate a safety impact. The most widespread surrogate safety measures (SSM) arising from traffic microsimulation and their definitions are presented below.

Table 3.5 Traffic Simulation Surrogate Safety Measures (adapted from (Federal Highway Administration, 2003))

Surrogate Safety Measure	Description
Gap Time (GT)	Time lapse between completion of encroachment by turning vehicle and the arrival time of crossing vehicle if they continue with same speed and path.
Encroachment Time (ET)	Time duration during which the turning vehicle infringes upon the right-of-way of through vehicle.

Deceleration Rate (DR)	Rate at which crossing vehicle must decelerate to avoid collision.
Proportion of Stopping Distance (PSD)	Ratio of distance available to manoeuvre to the distance remaining to the projected location of collision.
Post-Encroachment Time (PET)	Time lapse between end of encroachment of turning vehicle and the time that the through vehicle actually arrives at the potential point of collision.
Initially Attempted Post-Encroachment Time (IAPT)	Time lapse between commencement of encroachment by turning vehicle plus the expected time for the through vehicle to reach the point of collision and the completion time of encroachment by turning vehicle.
Time to Collision (TTC)	Expected time for two vehicles to collide if they remain at their present speed and on the same path.
DR distributions	Deceleration rate distributions
Required braking power distributions	Required braking power distribution needed in order to avoid an accident
Distribution of merge points	How merging areas are distributed across a motorway
Merge area encroachments	Merge area layouts
Gap-acceptance distributions	Distribution of the gap acceptance of vehicles
Number of vehicles caught in dilemma zones	Number of vehicles waiting in conflict areas in a simulation environment
Speed differential between crossing movements	Speed differences during crossing movements in intersections
Speed variance	Speed variance across and among lanes
Red- and yellow-light violations by phase	Red and yellow light violations by phase in urban road networks
Time-integrated and time-exposed TTC measures	(TET and TIT— duration of time that the TTC is less than a threshold and the integrated total TTC summation during that time, respectively)

Undoubtedly the two most widespread surrogate safety measures in the table above are Time to Collision and Post Encroachment Time.

Time to Collision (TTC) is definitely the most frequently used surrogate safety measure. Hayward, (1972) initially used TTC as a surrogate safety measure and defined it as the time required by two vehicles to collide if they remain on the same collision course and keeping the same speed. The mathematical formulation of TTC is presented below:

$$TTC = \begin{cases} \dfrac{x_l - x_f - L_l}{v_l - v_f} & , if\ v_F > v_L \\ \\ \infty & if\ v_{f\ \leq}\ v_L \end{cases} \tag{3.7}$$

In equation (3.7), $x_l - x_f$ depict the headway of two vehicles, L_l the length of the leading vehicle and $v_l - v_f$ the relevant velocity between the two vehicles in question. Obviously, TTC is non-negative value and hence cannot be defined when the speed of the leading or preceding vehicle is greater than the speed of the following vehicle as the two vehicles would be moving away from each other and therefore they wouldn't be on a collision course.

Post Encroachment Time (PET) is defined as the temporal difference between the moment a vehicle enters a conflict point until the time another vehicle arrives to this point (Cooper, 1984). It is more easily extracted than TTC because it does not require the indication of a collision course between vehicles neither it requires any speed or distance data. However special attention should be paid on the PET in the case of a motorway. The original definition of PET indicates a conflict point which can be seen with an X in Figure 3.6. For an equivalent motorway scenario the conflict point might be converted into a conflict line if the two vehicles participating in the conflict have approximately the same heading.

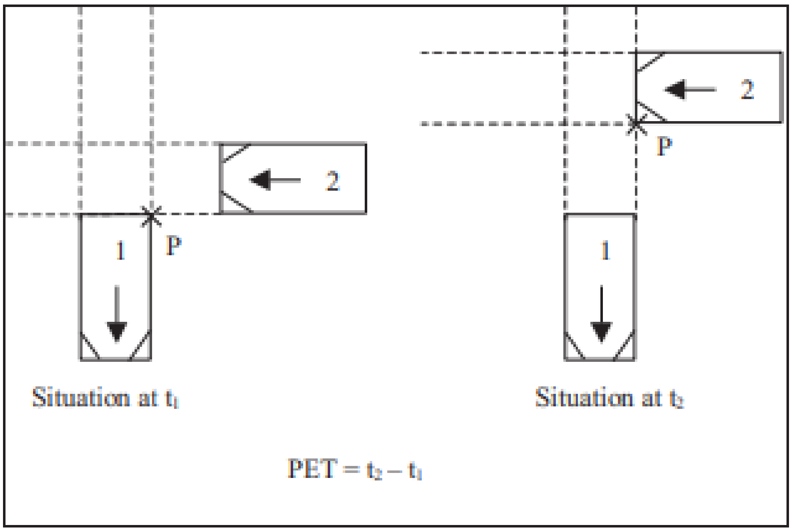


Figure 3.6 Definition of post encroachment time (Van Der Horst *et al.*, 2014)

With the most widespread SSMs being mentioned, it must be emphasized that them alone have been used as safety performance indicators in part of the existing literature (e.g. (Rahman and Abdel-Aty, 2018)). However, a better approach would include the inclusion of SSMs along with an evasive manoeuvre identification algorithm.

Therefore, Gettman *et al.*, (2008) investigated the potential use of surrogate safety measure thresholds along with vehicle trajectory data produced by traffic microsimulation in order to identify traffic conflicts. Their work resulted in the development of a widespread post-simulation processing tool called Surrogate Safety Assessment Model (SSAM) which is able to identify traffic conflicts using the SSMs TTC and PET along with vehicle trajectory data from microsimulation. SSAM is proven to be perhaps the only validated tool for identifying traffic conflicts from microsimulation and has been used widely in existing literature (Fan *et al.*, 2013; Habtemichael and Picado-Santos, 2013; Huang *et al.*, 2013; Morando, Truong and Vu, 2017; Katrakazas, Quddus and Chen, 2018; Rahman *et al.*, 2019b). The underlying traffic conflict identification algorithm of SSAM is analysed in section 4.3.2.

3.5 The Use of Statistics to Identify Underlying Factors of Simulated Safety

Despite all the efforts in conflict identification within traffic microsimulation, there is a lack of studies investigating the underling factors that affect the occurrence of conflicts in a simulation environment. So firstly, the need to investigate them is identified and secondly due to the lack of literature, in order to develop the appropriate methodology to identify the underlying factors of traffic conflict occurrence one should look into existing attempts explain accident occurrence which are proven to be related with traffic conflicts (see equation (3.6)).

3.5.1 Widespread safety related explanatory variables

Indeed, due to the immense losses to the society resulting from road accidents, literature has dedicated to efforts in investigating the underlying factors of accidents -instead of traffic conflicts- in order to provide guidelines for policymakers that would ameliorate the safety risks. These factors are referred to as crash precursors in existing literature (Kwak and Kho, 2016; Imprialou *et al.*, 2016).

Speed is the first factor that is linked with a large proportion of road accidents both in terms of accident severity (Imprialou *et al.*, 2016) as well as the risk of being involved in an accident (Elvik, Christensen and Amundsen, 2004). However, there are several conflicting conclusions in existing literature about whether speed itself or a by-product of speed – speed variance is actually affecting accident frequency.

Speed variance (also known as speed dispersion) is defined as speed differences within the same lane or across different lanes between individual vehicles or in a road section (Aarts and Van Schagen, 2006). High speed variance can result in more accident related interactions (Navon, 2003). One of the challenges regarding the inclusion of speed variance when trying to model its effect on safety, is the lack of individual vehicle-level speed data (e.g. vehicle trajectories) to calculate it effectively. Hence, the majority of studies defines speed variance as the standard deviation of speed (e.g. Taylor, 2000; Quddus, 2013). However, there is no consensus about whether speed variance significantly affects the occurrence of accidents and concerns are expressed about the use of speed variance as a precursor unless individual vehicle-level highly disaggregated data are used. Potentially, traffic microsimulation can excel in this regard as it can provide this kind of data. Although, in order for the speed variance measurements to accurately represent real-world conditions a speed-related calibration and validation of the microsimulation model should be performed.

Traffic flow is considered to be an additional widespread accident underlying factor. Rationally, there is a clear analogy between traffic flow and the number of vehicle interactions which could consequently lead to safety incidents and accidents (Navon, 2003). However, there are some studies which seem to disagree with this statement. For example, Garber and Ehrhart (2007) conclude that a relatively high traffic flow value per lane seems to affect accident risk negatively and Martin (2002) concludes that during off-peak times (low traffic flow values) more serious accidents tend to occur. The later can be justified by assuming that lower traffic flow values are associated with higher speeds and therefore higher speed variance. As of today, there seems to be a consensus regarding the overall effect of traffic flow on accidents by using the term "turbulence" of traffic flow which describes a situation where the normal traffic flow of a road network is disturbed by unusual events. Turbulences in the traffic flow are considered to be highly related with the occurrence of accidents (Abdel-Aty and Pande, 2005).

Other than metrics associated with vehicles' counts and kinematic characteristics, several factors associated with the infrastructure and more specifically road geometry have been identified to be related with accident frequency and accident severity in existing studies. More specifically, research has focused on the curvature, gradient, and the number of lanes of a road segment.

As far as curvature is concerned, sharp curves are linked with higher accident rates according to recent literature (Gitelman *et al.*, 2014). In practice, a sharp curve directly affects the sight distance of the driver, resulting in more driving errors and an increase in lateral acceleration which may lead to a failure in vehicle control. However, Chang (2005) argues that sharp curves with small radiuses causes drivers to drive more carefully if they are alerted of the potentially difficult driving environment in time. However, small curve radius values are not common in motorway environments.

High vertical grades are also a widespread factor related with accident frequency. Extended upgrades can lead to speed decreases, especially from heavy good vehicles leading to more passenger vehicles overtaking, increasing speed variance (Milton and Mannering, 1998a). This consequently can lead to more dangerous situations. On the other hand, extensive downgrade segments can lead to higher speeds and therefore more dangerous traffic conditions.

Finally, the number of lanes of a specific road segment can significantly affect road safety. More specifically, the number of lanes is associated with the number of lane changes and therefore with the number of vehicle interactions which can potentially prove to be dangerous. To be precise, (Kononov *et al*, 2008) modelled the relationship between possible vehicle conflicts as a function of the number of lanes in the following equation where C_n represents the number of possible conflicts and n the number of lanes.

$$C_n = \begin{cases} n * (n-1) & if\ n = 2 \\ n * (n-1) + \dfrac{n!}{3!\,(n-3)!} & if\ n > 3 \end{cases} \quad \textbf{(3.8)}$$

This equation seems to reflect the results of studies which concluded that the number of road lanes is related monotonically with accident frequency (e.g. Milton and Mannering, 1998). However, once again, results seem to be mixed and this is probably based on the context of each study. For example Ma and Kockelman, (2006) state that an increase in the number of lanes leads to a decrease in non-fatal accidents and that it has no effect on fatal accidents.

3.5.2 Statistical approaches in accident modelling

Due to the lack of studies investigating traffic conflict frequency, one should investigate the techniques applied in the past for the statistical modelling of accidents in order to identify appropriate method to model traffic conflicts. Retrospectively, through this thesis, similarities were observed between traffic conflict per hour and recorded accidents per year and hence investigating accident modelling techniques was deemed appropriate.

When analysing accident counts, important inherent data and methodological issues have been acknowledged by the literature. These issues may lead to errors when calculating a statistical model and may lead to inaccurate accident frequency predictions (Lord and Mannering, 2010): One of the most widespread issues in accident and hourly conflict data is the low sample mean. Accident or conflict observations are non-negative integers. More specifically, in most cases a large number of zeros are included in the data set which can cause significant problems in traditional linear regression models.

Additionally, in order to avoid information loss in spatiotemporally varying explanatory variables, data are often considered in small time intervals or in small space intervals. For example, a dataset describing the accidents occurring in a motorway that is divided in equal smaller segments may generate multiple observations of consequent segments which are highly correlated due to unobserved factors. This problem sets up correlation of disturbances among observations and results in parameter estimation problems (Washington, Karlaftis and Mannering, 2010).

Other examples of these issues are data over- (variance is greater than the mean) or under-dispersion, small sample size, under-reporting, endogenous variables and so on. In order to tackle the aforementioned issues, several statistical modelling approaches have been applied in the literature in order to overcome them. Lord and Mannering, (2010) in their paper summarise the most widespread existing models for analysing accident-frequency data.

Table 3.6 Summary of existing models for analysing crash-frequency data (Lord and Mannering, 2010)

Model type	**Advantages**	**Disadvantages**
Poisson	Most basic model; easy to estimate	Cannot handle over- and under-dispersion; negatively influenced by the low sample-mean and small sample size bias

Model type	Advantages	Disadvantages
Negative binomial/Poisson-gamma	Easy to estimate can account for over-dispersion	Cannot handle under-dispersion; can be adversely influenced by the low sample-mean and small sample size bias
Poisson-lognormal	More flexible than the Poisson-gamma to handle over-dispersion	Cannot handle under-dispersion; can be adversely influenced by the low sample-mean and small sample size bias (less than the Poisson-gamma), cannot estimate a varying dispersion parameter
Zero-inflated Poisson and negative binomial	Handles datasets that have a large number of zero-crash observations	Can create theoretical inconsistencies; zero-inflated negative binomial can be adversely influenced by the low sample-mean and small sample size bias
Conway–Maxwell–Poisson	Can handle under- and over-dispersion or combination of both using a variable dispersion (scaling) parameter	Could be negatively influenced by the low sample-mean and small sample size bias; no multivariate extensions available to date
Gamma	Can handle under-dispersed data	Dual-state model with one state having a long-term mean equal to zero
Generalized estimating equation	Can handle temporal correlation	May need to determine or evaluate the type of temporal correlation a priori; results sensitive to missing values
Generalized additive	More flexible than the traditional generalized estimating equation models; allows non-linear variable interactions	Relatively complex to implement; may not be easily transferable to other datasets
Random-effects	Handles temporal and spatial correlation	May not be easily transferable to other datasets
Negative multinomial	Can account for over-dispersion and serial correlation; panel count data	Cannot handle under-dispersion; can be adversely influenced by the low sample-mean and small sample size bias
Random-parameters	More flexible than the traditional fixed parameter models in	Complex estimation process; may not be easily transferable to other datasets

Model type	Advantages	Disadvantages
	accounting for unobserved heterogeneity	
Bivariate/multivariate	Can model different crash types simultaneously; more flexible functional form than the generalized estimating equation models (can use non-linear functions)	Complex estimation process; requires formulation of correlation matrix
Finite mixture/Markov switching	Can be used for analyzing sources of dispersion in the data	Complex estimation process; may not be easily transferable to other datasets
Duration	By considering the time between crashes (as opposed to crash frequency directly), allows for a very in-depth analysis of data and duration effects	Requires more detailed data than traditional crash-frequency models; time-varying explanatory variables are difficult to handle
Hierarchical /multilevel	Can handle temporal, spatial and other correlations among groups of observations	May not be easily transferable to other datasets; correlation results can be difficult to interpret
Neural network, Bayesian neural network, and support vector machine	Non-parametric approach does not require an assumption about distribution of data; flexible functional form; usually provides better statistical fit than traditional parametric models	Complex estimation process; may not be transferable to other datasets; work as black-boxes; may not have interpretable parameters

To conclude, in order to identify the appropriate statistical modelling approach to model traffic conflict data, the nature of the data must be investigated and described in depth so as to identify any underlying aforementioned issues. This will be done in section 4.3.2 of this thesis.

3.6 Knowledge Gap

Chapter 2 of this thesis revealed that CAVs are a rapidly evolving technology which is about to revolutionise existing transport systems as we know them. They promise to bring about compelling benefits on traffic, safety and the environment. They are complex entities comprising of several subsystems which control the main functionalities of the vehicle: sensing, perception, planning and control.

Following, chapter 3 identified that due to the lack of real-world CAV operational data, a large part of the research community has diverged from formerly established safety related evaluation methods to traffic simulation in order to evaluate their impacts. However, the same problem that has affected the shift from traditional methods to simulation is also the major overarching problem of CAV simulation studies. This lack of fundamental knowledge about how exactly CAVs will operate in the real world, that originates from the lack of CAV data, has led to severe uncertainty about the way that they should be simulated. Consequently, this uncertainty has led to assumptions, which in most cases are justified, in the current literature;

As mentioned previously, CAVs are complex and several subsystems rule their operations. Most of the existing studies focus on one subsystem - in most cases the control subsystem - or an element of the control subsystem such as the longitudinal control (car following) of the vehicle. Even though these studies provide a useful starting point, the narrow scope affects the reliability of the results. Most importantly, in this way, fundamental operational, technological and strategic challenges arising from CAV implementation are not covered. There is a need to address as many of those challenges as possible in a justified manner, in an integrated simulation environment in order to strengthen the reliability of simulation results.

Last but not least, even though it has been criticised for its effectiveness, traffic simulation has been proven useful in the past for safety evaluation purposes. Advanced traffic conflict identification algorithms and tools have been developed in order to facilitate and validate the evaluation process. Although research has put a large amount of effort in accident modelling, there is a lack of studies identifying the underlying factors – explanatory variables – that affect the occurrence of traffic conflicts within a microsimulation environment.

4 Research Methodology

4.1 Introduction

As section 3.6 underlined, existing approaches in CAV simulation are usually narrow in scope by focusing on specific functionalities of the control subsystem of a CAV and do not address fundamental technological operational and strategic challenges arising from their implementation. This work addresses this gap by developing an integrated CAV behaviour model which will address the following challenges:

a) Sensor error rates
b) Vehicle platoon size
c) High-level route-based decision making for CAVs

The developed algorithms are tested in a calibrated and validated motorway network using real world data which is the key to strengthen the reliability of the results (Katrakazas *et al*, 2018). More importantly, since the developed simulation framework is intended for safety evaluation purposes, a two stage calibration and validation process is followed using Time to Collision a safety measure of performance (Huang *et al.*, 2013). This thesis will present a novel safety calibration and validation method. It must be emphasized that only the human driving behaviour was calibrated due to lack of CAV data.

Finally, in order to advance the understanding of the occurrence of traffic conflicts within a traffic microsimulation environment, a robust statistical model is developed. More specifically, due to the nature of the simulated conflict data, a hierarchical Bayesian negative binomial regression model that takes into account spatial correlation is developed.

4.2 Research Design

The aim of this thesis is divided into six objectives which will be achieved through the methods outlined in Table 4.1. The first two objectives have been discussed in the literature review chapters 2 and 3.

Table 4.1 Research objectives and method per chapter

Objective	Method	Chapter
To identify issues and impacts of CAVs in mixed traffic streams	Literature Review	Chapter 2
To explore and review techniques used to evaluate the impact of Intelligent Transport Technologies and CAVs	Literature Review	Chapter 3
To develop a calibrated traffic microsimulation framework capable of simulating CAVs along with non-automated vehicles	Development of an integrated CAV simulation algorithm and implementing it in a calibrated traffic microsimulation environment	Chapter 4 and Chapter 5
To analyse the data from the microsimulation for the purpose of evaluating the impact on safety of CAVs	Development of a post simulation processing technique to calculate the safety impact of CAVs based on surrogate safety measures	Chapter 6
To assess underlying factors affecting the occurrence of traffic conflicts in a traffic simulation environment	Development of statistical models capable of handling the inherent limitations arising from the simulated traffic conflict data	Chapter 6
To recommend a number of specific scenarios where the safety benefit of CAVs would be maximized, specifically during the transition period	Estimation of the safety benefit per simulation scenario in order to provide recommendations for the real world implementation of CAVs	Chapter 6

4.3 Methods

4.3.1 Traffic Microsimulation

As mentioned previously, one of the objectives of this thesis is to develop an integrated simulation platform capable of simulating CAVs and their functionalities alongside conventional human traffic in a calibrated and validated motorway traffic microsimulation environment. Hence, it is understood that the main components of the simulation platform would be the motorway infrastructure, the human driven vehicles and CAVs. Consequently, this section of the thesis is divided into three sub sections:

a) Human driving behaviour
b) CAV driving behaviour and its functionalities
c) Motorway environment

The first two elements are described in this section of the thesis while the motorway study area along with the corresponding data used for its calibration and validation are described in detail in chapter 5 of this thesis.

The result of the review of existing traffic microsimulation software in section 3.3.2 indicated that the most appropriate software to be used in this thesis is the free-for-research purposes traffic microsimulation software PTV VISSIM. VISSIM is renowned for its ability to accommodate research projects and has been used extensively in existing literature (Fellendorf and Vortisch, 2001; Gomes, May and Horowitz, 2004; Gettman *et al.*, 2008; ATKINS, 2016b; Rahman *et al.*, 2019c).

The strength of microsimulation lies on its ability to simulate the behaviour of individual vehicles within a predefined road network. The behaviour and consequently the movement of each vehicle is ruled by a set of mathematical models which control the corresponding movement type. The two most important models are the car following model and the lane changing model. However, the previous statement applies mainly to human driven vehicles as the control algorithm of CAVs is arguably more complex. Hence the behaviour of a CAV will be described according to the simulation of its fundamental subsystems.

4.3.1.1.Human driving behaviour

The quality of the driver model is essential for the quality of the simulation tool (PTV AG, 2015). The human car following model in VISSIM is stochastic, time step based and microscopic, meaning that it treats driver-vehicle units as individuals. It is based on a psycho-physical car following model for longitudinal vehicle movement and a rule-based algorithm for lateral vehicle movement. These two components are the result of the work of Rainer Wiedemann who produced two versions of this model.

The first version was introduced in 1974 and was a simpler version – in terms of number of involved car behaviour parameters, while the later version in 1991 was more complex (Wiedemann, 1974). In this thesis the Wiedemann 99 (latter version) is used since it is more suitable for motorways and it is going to be described in detail below (Aghabayk *et al.*, 2013; PTV AG, 2016). Firstly, the longitudinal movement model is described in this section and the lane changing follows.

Wiedemann's model is based on the assumption that a vehicle inside a simulation environment can be in one of the following driving states:

- Free flow driving: The vehicle is not influenced by preceding vehicles. In this state, the driver seeks to reach and maintain his desired speed. In reality, the speed in this mode will oscillate around the desired speed due to imperfections in throttle control
- Approaching: This process describes the situation of the driver adapting his speed to according to the lower speed of the preceding vehicle.
- Following: The driver follows the preceding car without consciously accelerating or decelerating. He attempts to keep a constant safety distance. However, again due to imperfections, the speed difference oscillates around zero.
- Braking: Driver applies moderate to high deceleration rates if distance to the preceding vehicle falls below the desired safety distance. This situation can occur if the preceding vehicle abruptly brakes or changes its speed or a third vehicle changes lanes to squeeze in between two vehicles.

For each of the aforementioned driving states the acceleration is calculated as a result of the current speed, speed difference, distance to the preceding vehicle and individual driver and vehicle characteristics. The procedure of changing states follows a pattern according to predetermined thresholds which are shown in Figure 4.1 (Aghabayk *et al.*, 2013):

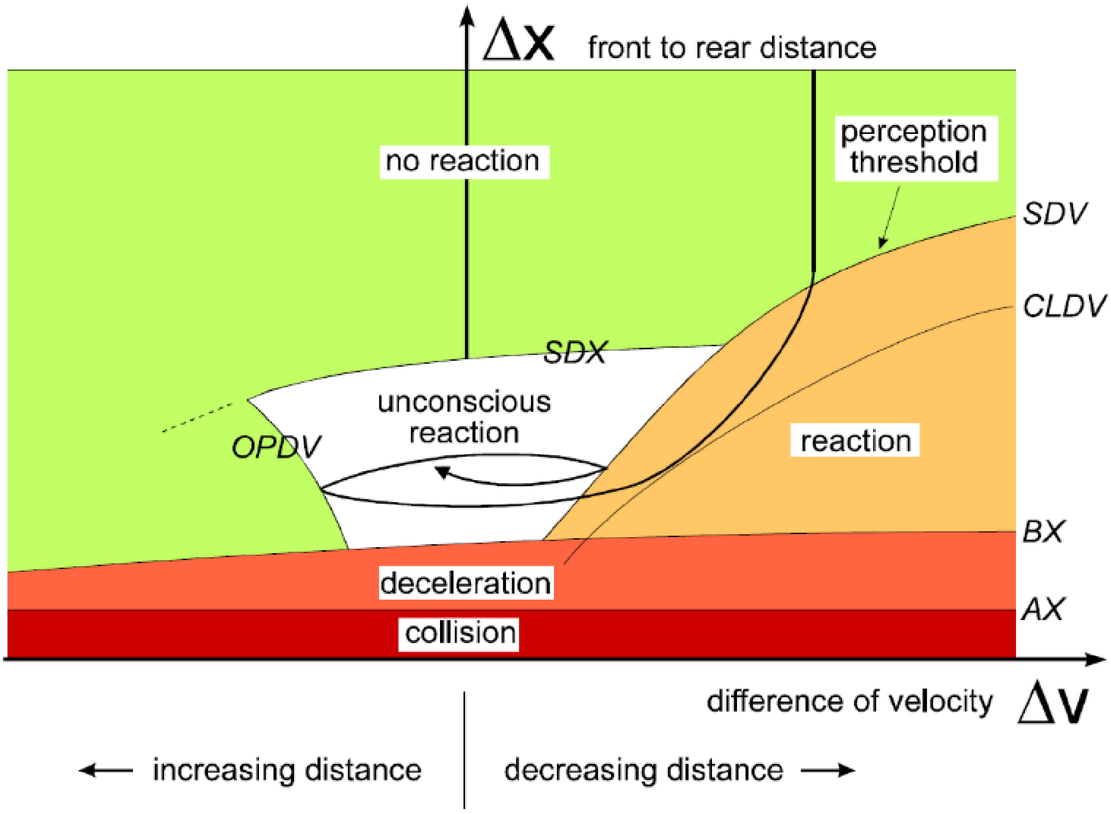


Figure 4.1 Wiedemann's car following behaviour of a vehicle (Aghabayk *et al*., 2013)

- AX: the desired distance between two stationary vehicles
- BX: the minimum following distance which is considered as a safe distance by drivers
- CLDV: the points at short distances where drivers perceive that their speeds are higher than their lead vehicle speeds
- SDV: the points at long distances where drivers perceive speed differences when they are approaching slower vehicles
- OPDV: the points at short distances where drivers perceive that they are travelling at a lower speed than their leader
- SDX: the maximum following distance indicating the upper limit of car-following process

These thresholds are not directly programmable in VISSIM. However, the user is able to calibrate them via a set of parameters. These parameters allow the user to calibrate the driving behaviour so as to represent the real-world traffic according to the available real world data. The list of these parameters is presented below:

Table 4.2 Parameters of the Wiedemann 99 car following model

Parameter	Unit	Description
CC0	m	Standstill distance: the average desired standstill distance between two vehicles. It has no variation.
CC1	s	Time headway: is the time (in seconds) that a driver wants to keep.
CC2	m	'Following' variation: restricts the longitudinal oscillation or how much more distance than the desired safety distance a driver allows before he intentionally moves closer to the car in front.
CC3	s	Threshold for entering car following mode in VISSIM: controls the start of the deceleration process, i.e. when a driver recognizes a preceding slower vehicle.
CC4	m/s	Following' thresholds: control the speed differences during the 'Following' state. Smaller values result in a more sensitive reaction of drivers to accelerations or decelerations of the preceding car
CC5	m/s	
CC6	1/(m*s)	Speed dependency of oscillation: influence of distance on speed oscillation while in following process.
CC7	m/s^2	Oscillation acceleration: actual acceleration during the oscillation process.
CC8	m/s^2	Standstill acceleration: desired acceleration when starting from standstill
CC9	m/s^2	Acceleration at 80 km/h: desired acceleration at 80 km/h

The thresholds of the Wiedemann car following model and the aforementioned parameters are linked based on a set of equations.

$$AX = L + CC0 \quad \textbf{(4.1)}$$

where L is the length of the preceding vehicle

$$BX = AX + CC1 * v \quad \textbf{(4.2)}$$

where v is equal to ego-vehicle speed if it is slower than the preceding vehicle; otherwise it is equal to preceding vehicle speed with some random errors. The error is determined randomly by multiplying the speed difference between the two vehicles by a random number between -0.5 and 0.5.

$$SDX = BX + CC2 \quad \textbf{(4.3)}$$

$$SDV_i = -\frac{\Delta x - SDX_i}{CC3} - CC4 \tag{4.4}$$

where Δx is the space headway in meters between the ego-vehicle and the preceding vehicle.

$$CLDV = \frac{CC6}{17000} * (\Delta x - L)^2 - CC4 \tag{4.5}$$

$$OPDV = -\frac{CC6}{17000} * (\Delta x - L)^2 - \delta . CC5 \tag{4.6}$$

where δ is a dummy variable which is equal to 1 when the ego-vehicle speed is greater than CC5 and 0 otherwise.

The exact formulation of the equation that controls the speed and acceleration of a vehicle in the Wiedemann car-following model has been the subject of debate between researchers in the past few years. And this is mainly because the developer company of the software has declared that the equations are included in the closed source code of the software and they differ according to the aforementioned longitudinal behaviour states. However, researchers have attempted to derive the equations using Wiedemann's PhD thesis (Gao and Rakha, 2008; Zhu *et al.*, 2018) however, there is no robust evidence that these are indeed the underlying equations. The equation is presented below:

$$u_n(t + \Delta t) = min \begin{cases} u_n(t) + 3.6 * \left(CC8 + \frac{CC8 - CC9}{80} * u_n(t) \right) \Delta t \\ 3.6 * \frac{s_n(t) - CC0 - L_{n-1}}{u_n(t)} \end{cases} , u_f \tag{4.7}$$

where $u_n(t + \Delta t)$ is the speed of the ego-vehicle in the next timestep t+Δt, $s_n(t)$ is the space headway between the ego vehicle and the preceding vehicle at time t, $u_n(t)$ the speed of the ego-vehicle in the current simulation time step, u_f the space-mean traffic stream free-flow speed in km/hour and L_{n-1} the length of the preceding vehicle. CC8, CC9 and CC0 follow the definitions presented in Table 4.2.

Equation (4.7) is twofold, meaning that the vehicle speed in VISSIM is computed as the minimum of two speeds. The upper part of the bracket represents the vehicle acceleration restrictions based on the kinematic characteristics of the vehicle itself. CC8 for example represents a vehicle kinematics model with a linear speed-acceleration relationship where CC8 is the maximum vehicle acceleration at a speed of 0 km/h and CC9 is the maximum vehicle acceleration at a speed of 80 km/h in m/s^2. The lower part of the bracket of equation (4.7) is a steady-state car-following model.

VISSIM is a time-step based simulation software. This means that the state of the simulation vehicles is updated on predefined time intervals. The higher the simulation frequency (smaller timestep) the more detailed and accurate it is. The most common simulation frequency value in the literature is 10 Hz and the same value is selected for this thesis. Given the above thresholds and equations, the software calculates the speed and consequently the acceleration of each vehicle inside the simulated network and updates the state and location of each simulation vehicle at every time step.

Vehicle lateral behaviour and consequently lane changing in a motorway environment in VISSIM is divided into two main categories; necessary (mandatory) lane changes and free lane changes (PTV AG, 2015). Necessary lane changes take place in order to reach the next link (segment) of a predefined route. The driving behaviour parameters for this type of lane change contain the maximum acceptable deceleration of the lane changing vehicle and the vehicle that will be its follower in the target lane. Target lane is defined as the lane that the ego-vehicle wants to move into. The second category of lane change, the free lane change is a lane change that a vehicle performs in order to obtain speed advantages or more space. The prerequisite for this type of lane change to take place is the desired safety distance in the target lane. The desired safety distance is determined by the speed of the lane changing vehicle and the preceding vehicle in the target lane. The user cannot influence the degree of aggressiveness for free lane changes meaning, how often will a driver select to perform it. However, the user can influence free lane changes by adapting the safety distance.

For both of the types of lane change in VISSIM the vehicle needs to find a suitable gap in the direction of travel. The gap size depends on two speeds: the speed of the lane changing vehicle and the speed of the vehicle approaching from behind in the target lane. The software contains a number of parameters which can be adjusted by the user for the lane changing behaviour. The most relevant to these study parameters are presented in Table 4.3.

Table 4.3 Lane changing parameters in PTV VISSIM

Element	Description
Diffusion time	The maximum amount of time a vehicle can wait at the emergency stop distance for a necessary change of lanes. An emergency stop is performed when the vehicle does not detect a suitable gap to perform a necessary lane change. When this time is reached the vehicle is removed the network, at the same time a warning is written to the **.err* file and displayed in the **Messages** window.
Min. headway	The minimum distance between two vehicles that must be available after a lane change, so that the change can take place (default value 0.5 m). A lane change during normal traffic flow might require a greater minimum distance between vehicles in order to maintain the speed-dependent safety distance.
To slower lane if collision time is above	**Free driving time** : only for **Slow lane rule** or **Fast lane rule**: defines the minimum distance to a vehicle in front, in seconds, which must be present on the slower lane, so that an overtaking vehicle switches to the slower lane.
Safety distance reduction factor:	**Safety distance reduction factor (lane change)**, (**SafeDistRedFact**): is taken into account for each lane change. It concerns the following parameters: The safety distance of the trailing vehicle on the new lane for determining whether a lane change will be carried out The safety distance of the lane changer itself The distance to the preceding, slower lane changer During the lane change Vissim reduces the safety distance to the value that results from the following multiplication: *Original safety distance • safety distance reduction factor* The default value of 0.6 reduces the safety distance by 40%. Once a lane change is completed, the original safety distance is taken into account again.
Cooperative lane change	**Cooperative lane change** (**CoopLnChg**): If vehicle **A** observes that a leading vehicle **B** on the adjacent lane wants to change to his lane **A**, then vehicle **A** will try to change lanes itself to the next lane in order to facilitate lane changing for vehicle **B**. For example, vehicle **A** would switch from the right to the left lane when vehicle **B** would like to switch to the left from a merging lane to the right lane.
Maximum deceleration for cooperative braking	**Maximum cooperative deceleration** (**CoopDecel**): Specifies to what extent the trailing vehicle **A** is braking cooperatively, so as to allow a preceding vehicle **B** to change lanes into its own lane.
Overtake reduced	If this option is selected, vehicles immediately upstream of a reduced speed area may perform a free lane change If it is not selected, vehicles never start a free lane change directly upstream of a reduced speed area.
Advanced merging	If this option is selected, vehicle can perform lane changes earlier. Thus, the capacity increases and the probability that the vehicles come to a stop to wait for a gap decreases

The lateral and lane changing behaviour of a vehicle and the parameters associated with it within a traffic microsimulation software, have always been a challenge to calibrate. And this is mainly because even though some of them are based on high level observation of the behaviour of drivers in a network (such as cooperative lane change) not all the drivers of the network are operating according to the rule. Additionally, some other parameters, such as safety distance reduction factor which is the most used in existing literature for calibrating lane changing behaviour, are very hard to obtain sufficient real-world data to calibrate on. These data would have to be naturalistic driving data combined with radar data for a large representative sample of drivers in a representative sample of lane change situations. Hence, the biggest part of the literature focuses on car following parameters (Habtemichael and Picado-Santos, 2013).

4.3.1.2. Calibration and validation of the human driving behaviour

Calibration is defined as the adjustment of the simulation model parameters to enhance a model's capacity to replicate real world driving behaviour and traffic characteristics. As section 4.3.1.1 revealed, there is a plethora of simulation parameters which can potentially be adapted in order to achieve the required real-world representation. Figure 4.2 presents a general framework of the calibration process. The calibration process is an iterative process which can be considered as an optimisation problem which seeks to minimize the deviation between observed and corresponding simulated measurements.

The process starts by a default set of parameters which are usually set by the microsimulation software. Subsequently, the real-world data for the simulated environment are input into the simulation software in various form. This will be analysed further in chapter 5 of this thesis. Afterwards, an initial number of simulation runs are performed in order to obtain a dataset which is used for comparison with the real-world observed measurements. The simulated measurements are compared with the calibration measurements and if the error is acceptable, the process is terminated, and the selected parameters are validated by comparing the simulated dataset with a validation dataset originating from the initial real-world data. If the error is not acceptable the calibration process is repeated with a selection of different calibration parameters.

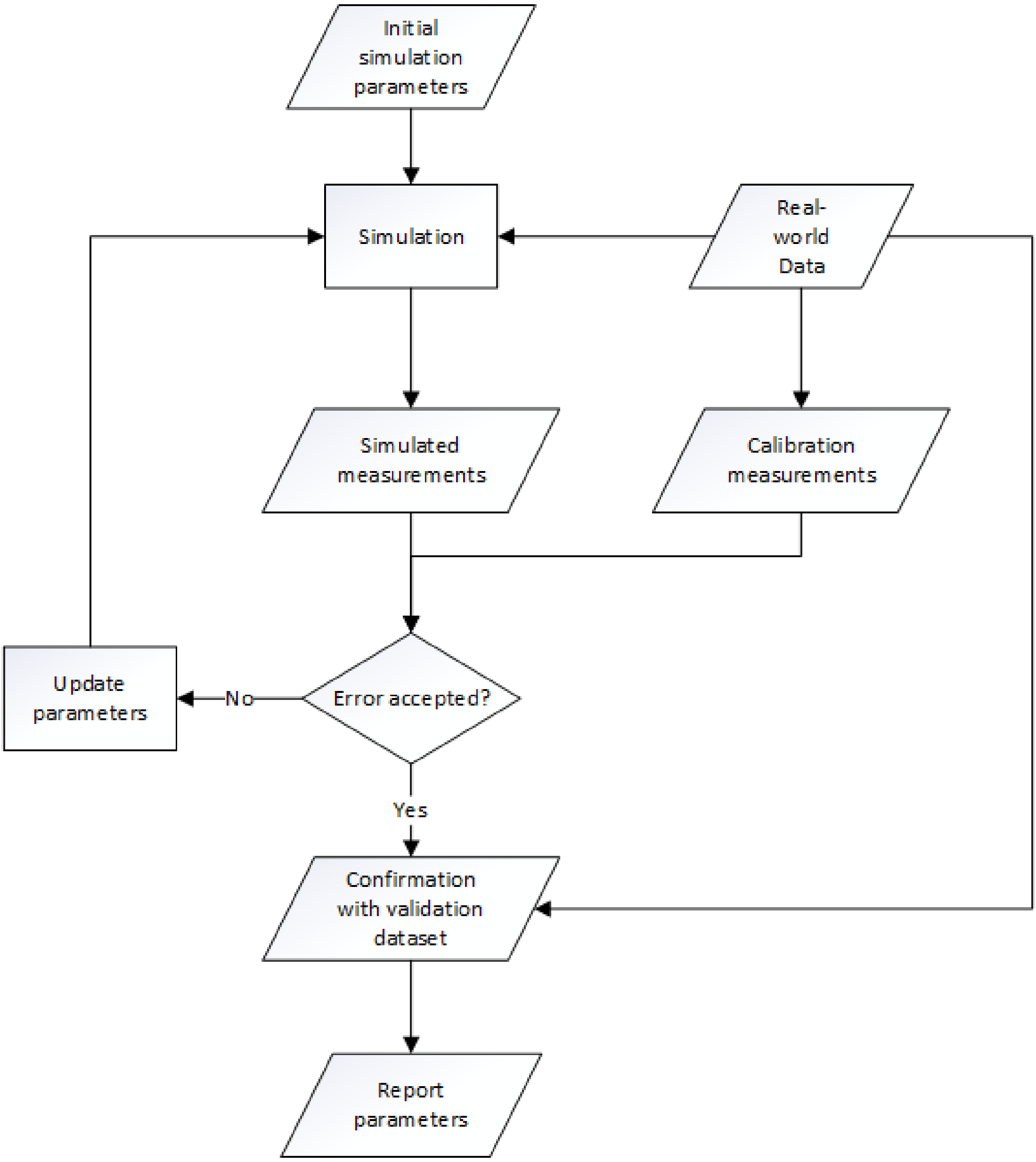


Figure 4.2 General framework of microsimulation calibration process

The calibration process described above is followed in the majority of the studies which perform an evaluation of an intervention within the simulation software from a traffic point of view. However, recent safety evaluation studies have emphasized that in order for traffic simulation to produce a reliable safety result, a two stage calibration process must be followed in order to calibrate both for traffic and safety parameters (Fan *et al.*, 2013; Huang *et al.*, 2013). In this way, the process described above is performed two times.

According to the above, a two-stage calibration and validation approach is followed for this thesis. The models developed, are calibrated for the times of data availability; between 11:00 and 12:00 a.m. The number of simulation iterations (runs) needed in order to achieve a 95% confidence interval level for the simulation output is calculated using Equation (4.8) (Shahdah, Saccomanno and Persaud, 2015). In this equation, N equals the required number of simulation runs, σ equals the sample standard deviation of the simulation output, t is the student's t-statistic for two-sided error of a α/2 with N-1 degrees of freedom and E equals the allowed error range. The result showed that 15 simulation runs were sufficient and were conducted for each calibration and validation stage.

$$N = \left(\frac{t_{\left(1-\frac{\alpha}{2}\right),N-1} * \sigma}{E} \right)^2 \tag{4.8}$$

The first stage of the calibration of the microsimulation model in this thesis is conducted in order to ensure that traffic performance measures such as traffic volume, speed or travel time are reproduced reasonably in the simulation. The data for this stage of calibration come from inductive loop detectors in the study area. Following guidelines provided by FHWA (Dowling, Skabardonis and Alexiadis, 2004), the chosen measures of performance are travel time and traffic flow. According to these guidelines for travel time calibration, simulated values should be within a range of ± 15% of the observed values for more than 85% of the observation pairs. On the other hand, in order to calibrate traffic volume values, the GEH statistic is used. The GEH statistic is presented in equation (4.9) where E stands for the simulated traffic volume and V is the observed values. In order for the calibration process to be successful, the GEH statistic should be less than 5 for 85% of the observation pairs (simulated versus real world). The results of the first stage calibration are presented in section 5.2 of this thesis.

$$GEH = \sqrt{\frac{(E-V)^2}{\frac{E+V}{2}}} \tag{4.9}$$

Subsequently, the second stage of the calibration ensured that safety parameters were accurately simulated in the network. The majority of studies following two-stage calibration approach chose their safety measure of performance according to the available data. Namely, Fan *et al.,* (2013) and Huang *et al.*, (2013) use the number of simulated conflicts as a measure of performance. However, this approach has limitations, as the number of real-world conflicts was calculated using manual human observation which can consist the characterisation of the conflicts objective. Rahman *et al.*, (2018) use the standard deviation of speeds as a measure of safety performance to calibrate the models developed in terms of safety, however, there is no clear indication that standard deviation of speeds affects safety in their study.A novel calibration process is followed in this thesis.

The measure of safety chosen for this thesis is the Time To Collision (TTC) (see equation (3.7)) distribution. A TTC distribution calculated from data gathered through Loughborough University's instrumented vehicle is compared with TTC distributions calculated from vehicles in VISSIM. The two statistical distributions are compared using the non-parametric Mann-Whitney U test. This statistical test is deemed appropriate for this comparison as it does not require the assumption that the two distributions follow the normal distribution. The null hypothesis of this test is as follows:

h_0: The distributions of both populations are equal

h_a: The distributions are not equal

The test involves the calculation of the U statistic whose distribution under the null hypothesis is known. According to the value of the U statistic, different conclusions can be drawn and reject or fail to reject the null hypothesis.

$$U = n_1 * n_2 + \frac{n_2 * (n_2 + 1)}{2} - \sum_{i=n_1}^{n_2} R_i \quad \textbf{(4.10)}$$

In equation (4.10) U is the Mann-Whitney U statistic, n1 the sample size of the first sample, n2 the size of the second sample and Ri the rank of the sample size. Same as above, the data collection procedure and the result of the second stage of the calibration are presented in section 5.3. Finally, the overall calibration approach is presented in Figure 4.3.

Figure 4.3 Calibration and validation approach followed in this thesis

4.3.1.3. CAV driving behaviour

Human driving behaviour within VISSIM was analysed in section 4.3.1.1 and was organised according to the type of movement of the ego-vehicle; longitudinal or lateral movement. However, as underlined in section 2.2.5 CAVs are complex entities which consist of multiple subsystems which rule their movement. Hence, the human driver model is not representative of CAV driving and it is deemed necessary that the programming of the CAV behaviour follows closely the operation of these subsystems. The tool used for this thesis should be able to approach and simulate the functionalities of CAVs and their subsystems and allow a high degree of flexibility. As presented in section 3.3.2 the majority of available and widespread traffic microsimulation tools were evaluated. It was considered that the External Driver Model API of PTV VISSIM provided the required interface in order to approximate the functionality of all CAV subsystem. Hence, this section will describe how each of these subsystems, sensing, perception, planning and control are simulated in the simulation software.

In general, the CAV driving behaviour and consequently the CAV control algorithm is developed in the Application Programming Interface (API) of PTV VISSIM. This tool is also known as External Driver Model Dynamic Link Library (DLL) interface and provides the option to the user to replace the internal behaviour of the vehicle with a fully user-defined behaviour for certain types or all of the simulated vehicles. The API is written in C/C++ and a corresponding compiler (usually Microsoft Visual

Studio). The API contains specific functions which are going to be described below (PTV AG, 2010).

During the simulation run, VISSIM communicates with the API code during every simulation step for every vehicle that the API code has been assigned. VISSIM sends the current state of the vehicle and its surroundings to the API and the API calculates the acceleration/deceleration of the vehicle as well as the lateral behaviour (lane changes) and sends these calculations back to VISSIM to be used in the current time step. The developed API can be assigned to a specific type of vehicle in the simulation software by selecting the corresponding option in the graphical user interface of VISSIM. Hence, the developed algorithm was assigned to a specific CAV-type vehicle which in terms of geometry was similar to a typical vehicle.

The API contains 3 main functions which have specific roles in the API:

Initially, the DriverModelSetValue function is described. This function is responsible to read the current value of the data items from VISSIM indicated by type and indexed by the operators index1 and index2. The value is passed to the API for calculations as a long (integer) value, double (decimals) value and string (text). The code makes sure to save the value somewhere if it is required for later calculations.

The function must return 1 if the value is used by the API, otherwise it should return 0. Using this function, a number of variables can be extracted from VISSIM for the vehicle that is controlled by the API.

- Vehicle path
- Simulation frequency
- Current simulation time
- Vehicle ID
- Current lane
- Odometer reading
- Lane angle
- Lateral position
- Velocity
- Acceleration
- Vehicle geometric characteristics
- Maximum allowed acceleration
- Desired velocity
- Vehicle colour

- Nearby vehicles ID
- Nearby vehicles geometric characteristics
- Active lane change
- Nearby vehicles distance
- Nearby vehicles velocity
- Number of lanes in the current link
- Desired acceleration

The next function DriverModelGetValue, helps VISSIM retrieve values of the data items indicated by type and indexed by index1 and index2. The function must return 1 if this value is to be sent to VISSIM.

The main variables that are sent back to VISSIM from the API are the desired acceleration which ultimately controls the longitudinal movement of the vehicle and the active lane integer variable which controlled the lane changing movement of the vehicle.

Last but not least the DriverModelExecuteCommand function is responsible for all the calculations that are being conducted by the API. This function contains three main commands; INIT, CREATE_DRIVER, KILL_DRIVER and MOVE_DRIVER. The INIT command is executed at the start of a VISSIM simulation run to initialize the driver model API and DriverModelSetValue and DriverModelGetValue functions are called simultaneously to obtain the first readings from the simulation software. Subsequently, the command CREATE_DRIVER is executed whenever a new vehicle is set into the network in VISSIM. Same as above the other two functions are called to get measurements for the new vehicle. The command KILL_DRIVER is called from VISSIM when a vehicle reaches its destination and thus leaves the network.

Perhaps the most important function above is the MOVE_DRIVER function which performs all the calculations for the vehicle controlled by the API. This command is executed by the API during every simulation step in order to calculate the kinematic characteristics of the ego -vehicle namely acceleration and active lane change. Using this command, the algorithm outlining the functionality of the CAV subsystem is developed and is presented below:

Sensing and perception subsystem

As the literature review of the thesis identified, the sensing subsystem of a CAV uses a variety of vehicle sensors such as radar, lidar and camera and communication equipment for raw data gathering (i.e. spatio-temporal positions, trajectory, kinematics, surrounding traffic characteristics, and destinations), while the perception subsystem translates the raw data into useful information about the vehicle and its surroundings. This behaviour is programmed in this thesis as follows:

According to the latest version of PTV VISSIM, the API-controlled vehicle can scan surrounding traffic up to an infinite range. Each vehicle in the simulation network is given a specific set of coordinates (index1, index2) which are relative to the API-controlled vehicle. Index1 indicates the lane that the nearby vehicle runs on; a value of zero means that the nearby vehicle was in the same lane as the API-controlled vehicle, a value of +1 and -1 means the nearby vehicle runs on the first lane on the left or right accordingly. Index 2 represents the relative longitudinal position compared to the API-controlled vehicle; a value of +1 and -1 means the nearby vehicle is the next vehicle downstream and upstream accordingly whereas +2 or -2 means the nearby vehicle is the second next downstream or upstream accordingly. As the sensors of CAVs do not have an infinite scanning range, the detection range of the API-controlled vehicle in this study is programmed to represent the scanning range of a typical radar sensor (200 m)(Continental, 2012). For a visual representation of this scanning process see Figure 4.4.

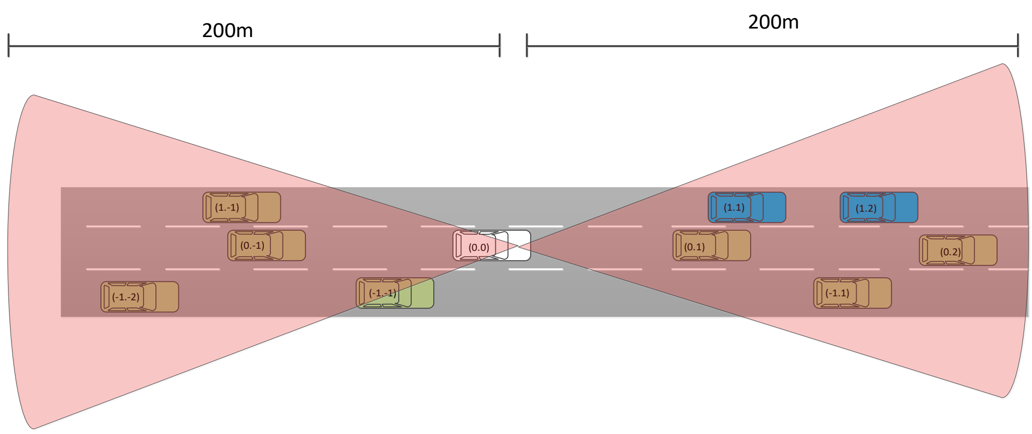


Figure 4.4 Vehicle scanning process in PTV VISSIM EDM API

The raw data gathered initially by the API include 100% accurate surrounding vehicles' relative speed, distance, lane and destination data. This may not be realistic as real-world sensors are characterised by their operating limits where anomalies are inevitable. Hasch *et al.*, (2012) indicate that a typical distance and inaccuracy value of a generic long radar sensor is 0.1m and 0.1 m/s while the manual of a typical automotive long range radar specifies that inaccuracy values might reach 0.25m and 0.14 m/s accordingly (Continental, 2012). There is lack of information on how this error in the radar measurements is distributed and there are significant differences in distance accuracy measurements. According to Zhou *et al.*, (2017), a reasonable assumption is that the error follows a normal distribution.

Considering the above, a first group of scenarios to be tested is defined, that can address a first technological challenge arising by the use of sensors in traffic microsimulation. Since 95% of the observations (sensor measurements in this case) of a normal distribution fall within the range of two standard deviations from the mean (i.e.$\mu \pm 2\sigma$), the standard deviation of the sensor errors with respect to distance and speed measurements pairings (i.e. distance s.d, speed s.d.) are selected; (0.05m, 0.05 m/s), (0.1m, 0.06m/s), (0.15m, 0.07m/s) and (0.2m, 0.08m/s). These sensor error values are examined. Subsequently, the developed API converted the raw measurements into useful data that are used from the planning and control subsystem. The code that allowed for this to happen in the API can be found in the appendix of this thesis

The value “error1” was then added to the measurements derived from VISSIM before they were used for calculations. Specifically, they were added to the net distance, the time gap and the desired distance to the preceding vehicle are calculated to be used by the planning and control subsystems.

Planning and control subsystems

The planning subsystem in a real-world CAV usually includes trajectory planners and behaviour planners, whereas the control subsystem includes the actuators and commands to drive the car.

Starting with the planning subsystem, in this thesis, CAVs are programmed to follow a high-level route-based decision-making algorithm. The flowchart of this route-based decision-making algorithm is presented in Figure 4.8 and the code is presented below. According to this algorithm, CAVs dynamically select the travelling lanes according to their path planning. For example, if according to the data gathered from VISSIM, the destination of the API-controlled vehicle is one of the two next off-ramps of the motorway, the CAVs chose to drive in the outermost lane of the motorway. Otherwise, the CAV can select between the rest of the lanes of the motorway. In this case, if the API-controlled vehicle is, for example, driving in the middle lane of a 3-lane motorway and the preceding vehicle is not a CAV and a leading CAV is identified in the outermost lane, a lane change is initiated in order to form a vehicle platoon in the outermost lane (see Figure 4.5). Adjacent CAVs could be identified from the API-controlled vehicle due to a user-defined attribute programmed in the C++ code.

This high-level route-choice plan results in even traffic flow distribution across lanes and formulation of CAV platoons with similar destinations. Consequently, platoon dissolving happens less frequently and ultimately less disruptions on the traffic flow of the motorway are caused by last minute lane changes.

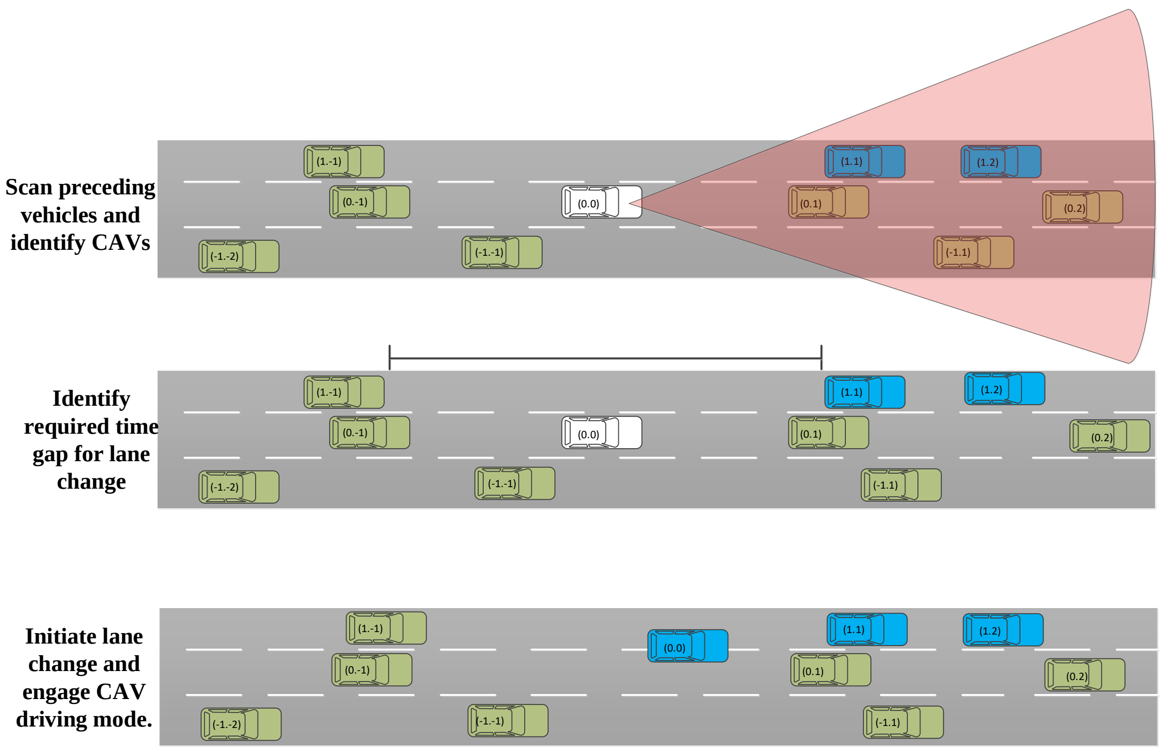


Figure 4.5 Step-by-step platoon formulation through the proposed CAV control algorithm

In addition to the lane changes initiated due to the route-based decision-making algorithm, CAVs can perform a lane change in order to merge in and diverge from the motorway. A lane changing manoeuvre is initiated through the control algorithm of the designed API, if the predefined time gap in the target lane was found. For all the lane changes described above, the required time gap that is set is 0.6 seconds from the vehicle upstream and downstream in the target lane. This value was set based on the car following distance of CAVs discussed below and relevant literature (Chen *et al.*, 2017). However, it must be emphasized that there is no clear recommendation in the literature with regards to the optimal gap acceptance for CAV lane changing. Surrounding traffic (both CAVs and human-driven vehicles) were programmed to facilitate the lane change process by decelerating if a CAV with intention to change lane is identified in an adjacent lane. The lane changing parameters such as lane angle and number of target lane, are controlled by VISSIM.

Once the CAV is driving in the lane defined by the route planner, a longitudinal constant time gap control algorithm controls the acceleration and as a result, the speed of the vehicle. The high-level result of the proposed constant time gap algorithm is that CAVs are able to drive closer to their preceding vehicles compared to human drivers with less oscillation in the distance kept, ultimately forming vehicle platoons with other CAVs. The accepted car-following time-gap chosen for this study was 0.6 seconds, which is in-line with relevant literature (e.g. ((ATKINS, 2016b; Rahman and Abdel-Aty, 2018; Stanek *et al.*, 2018)). This time-gap is achieved by calculating the acceleration or deceleration of each of the dll controlled vehicles, for each simulation time step, as follows. The acceleration or deceleration of a vehicle in VISSIM during each time step is defined by equation (4.11).

$$a = \frac{\Delta \upsilon}{\Delta t} \tag{4.11}$$

where $\Delta\upsilon$ is the difference between current speed and target speed and Δt is the time step of the simulation, in this case 0.1 sec. Assuming that the dll controlled vehicle is not following the preceding vehicle with the desired time gap (d) - a situation which is graphically described in Figure 4.6 - the distance travelled by both cars (x1,x2) and the time gap during time step t and time step t + 0.1 can be defined by equations (4.12), (4.13) and (4.14).

$$x_1 = u_1 * t + \frac{1}{2} * a_1 * t^2 \qquad (4.12)$$

$$x_2 = u_2 * t + \frac{1}{2} * a_2 * t^2 \qquad (4.13)$$

$$d = x_2 + D - x_1 \qquad (4.14)$$

By subtracting equation (4.12) from equation (4.13) and taking into account that the target final speed u_1' of the dll-controlled vehicle is the speed of the preceding vehicle (in order to reach the predefined time gap having the same speed as the preceding vehicle and thus form the platoon), equation (4.15) and subsequently (4.16) are calculated, assuming that the initial speed of the leading vehicle u_2, and the speed of the vehicle at the back, u_1 are not equal. In equation (4.16) , a_1' represents the acceleration of the CAV in order to achieve the desired time gap.

$$t = \frac{2 * (x_2 - x_1)}{u_2 - u_1} \qquad (4.15)$$

$$a_1' = \frac{(u_2 - u_1)^2}{2 * (x_2 - x_1)} \qquad (4.16)$$

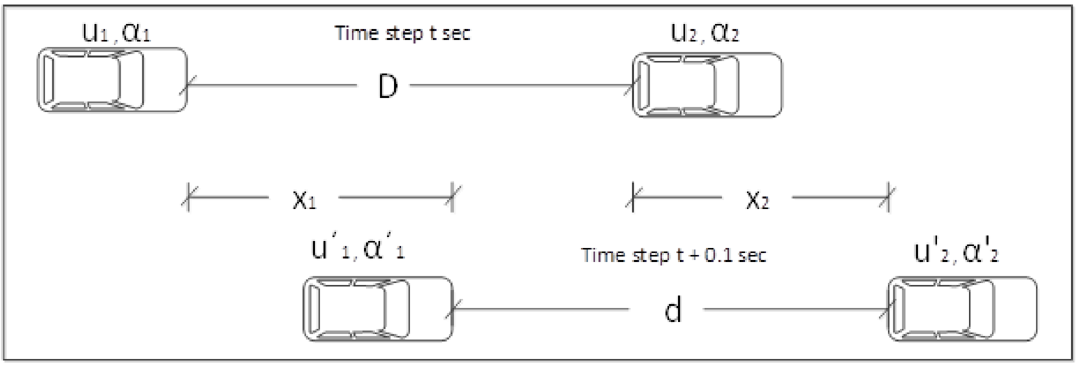


Figure 4.6 Desired and actual distance diagram for ego vehicle acceleration/deceleration calculation

All vehicles controlled by the API continuously adjust their acceleration according to equation (4.16). It must be noted that the aforementioned acceleration/deceleration calculation only starts when the preceding vehicle in the same lane as the dll-controlled vehicle is a CAV vehicle. Otherwise, the CAV applied the same rule but aiming to keep a time gap according to the real-world human data. In this study, the type of preceding vehicle and the exact measurements of vehicle velocity, acceleration, deceleration and distance are directly communicated between the ego-vehicle and the preceding vehicle through the simulation software. In the real world, this would happen through a communication channel between the two vehicles. Hence, it can be assumed that these two vehicles are connected to each other and ultimately form a vehicle platoon. Finally, the upper limit of the acceleration and deceleration is set through the graphical user interface of PTV VISSIM to 1.5 m/sec2 and 2.5 m/sec2 accordingly, following recommendations from Talepbour et al. (2016). The platoons which were formed in VISSIM a result of the process described above can be observed in Figure 4.7.

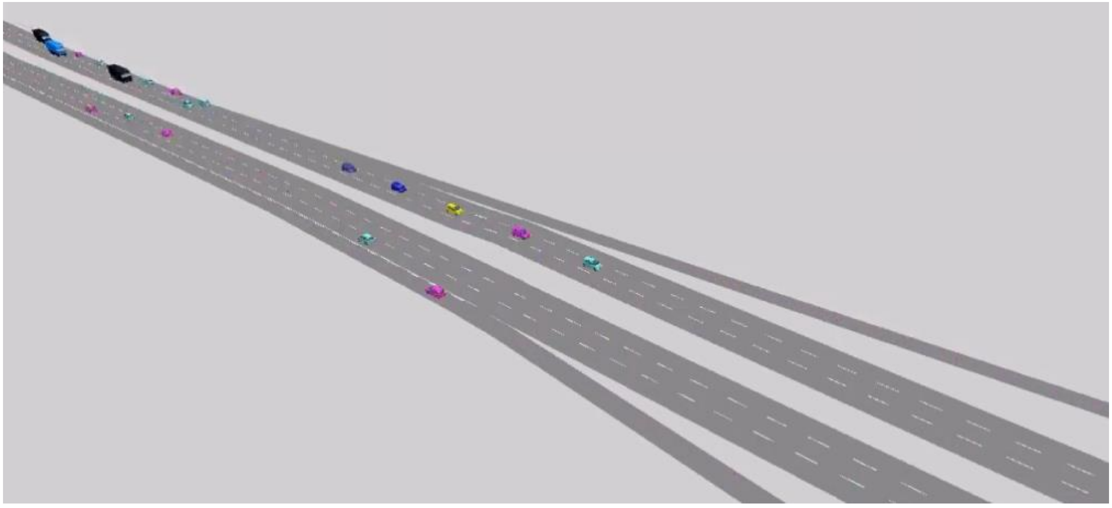


Figure 4.7 A vehicle platoon as it appeared in VISSIM

As mentioned above, following equation (4.16) vehicles were able to form vehicle platoons. This thesis evaluates the impact of platoon size on motorway safety as it was defined as an operational and strategical challenge arising from CATS in the literature review chapter. The inter-platoon time gap was set to 3 seconds according to Varaiya, (1993), in order to allow conventional traffic to navigate between platoons. The platoon sizes tested are 3, 5, 7, and 9 vehicles for the different market penetration rates and the safety results are compared to the baseline scenario (no platoon size limit).

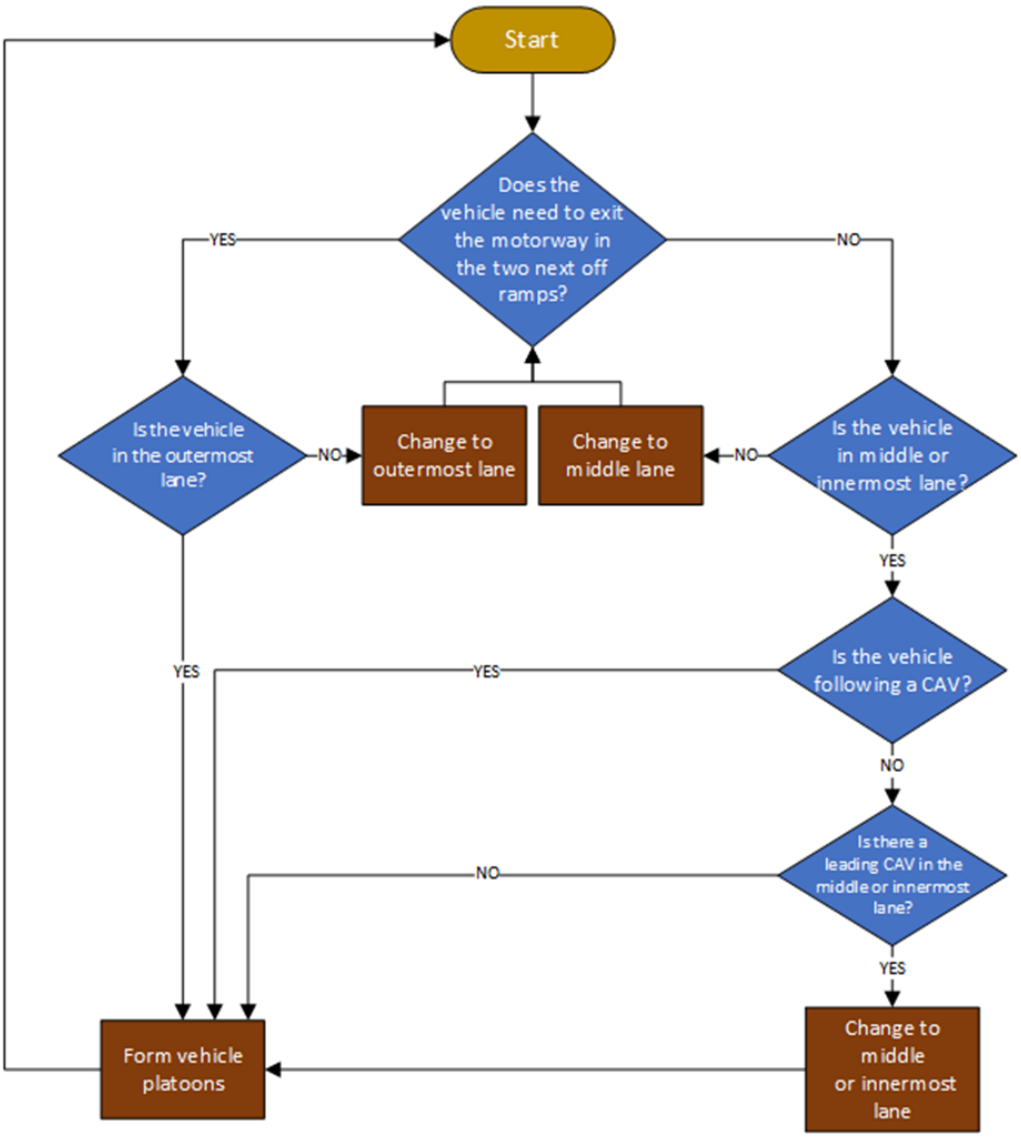


Figure 4.8 Flowchart of the CAV route-based decision making algorithms

Finally, with the CAV driving behaviour being described, it was deemed necessary to evaluate the safety impact of CAVs on various traffic conditions. Hence a number of scenarios were formulated based on the traffic flow measurements extracted for each different weekday due to real-world data limitations explained in Chapter 5. It must be noted that all the aforementioned investigated scenarios are ran, ceteris paribus, across different market penetration rates. That means that when the safety impact of sensor error is investigated, the platoon size is not considered in the experiment and so on. The tested scenarios are summarised in Table 4.4. It must be emphasized that the number of simulation runs performed for each scenario was 15 according to equation (4.8) (see section 4.3.1.2).

Table 4.4 CAV Simulation Scenarios in this thesis

Scenario number	CAV Market Penetration Rates tested	Sensor error		Platoon size (vehicles)	Average Traffic flow (veh/h)	Route-Based Decision-making algorithm
		Distance error s.d. (m)	Speed error s.d. (m/s)			
1 to 5	0, 25, 50, 75 and 100%	N/A	N/A	N/A	1673 (Monday)	No
6 to 10	0, 25, 50, 75 and 100%	N/A	N/A	N/A	1495 (Tuesday)	No
11 to 15	0, 25, 50, 75 and 100%	N/A	N/A	N/A	1545 (Wednesday)	No
16 to 20	0, 25, 50, 75 and 100%	N/A	N/A	N/A	1568 (Thursday)	No
21 to 25	0, 25, 50, 75 and 100%	N/A	N/A	N/A	2049 (Friday)	No
26 to 29	25, 50, 75 and 100%	N/A	N/A	N/A	1545 (Wednesday)	Yes
30 to 33	25, 50, 75 and 100%	0.05	0.05	N/A	1545 (Wednesday)	No
34 to 37	25, 50, 75 and 100%	0.10	0.06	N/A	1545 (Wednesday)	No
38 to 41	25, 50, 75 and 100%	0.15	0.07	N/A	1545 (Wednesday)	No
42 to 45	25, 50, 75 and 100%	0.20	0.08	N/A	1545 (Wednesday)	No
46 to 49	25, 50, 75 and 100%	N/A	N/A	3	1545 (Wednesday)	No
50 to 53	25, 50, 75 and 100%	N/A	N/A	5	1545 (Wednesday)	No
54 to 57	25, 50, 75 and 100%	N/A	N/A	7	1545 (Wednesday)	No
58 to 61	25, 50, 75 and 100%	N/A	N/A	9	1545 (Wednesday)	No

4.3.2 Conflict identification process

Since the participating simulation vehicles, algorithms and scenarios are defined above, the conflict identification process in order to evaluate the safety impact of the developed CAV algorithms remain to be discussed.

Section 3.4 concluded that a widespread approach for safety evaluation has been the identification of conflicts from traffic microsimulation through a post processing software developed by Federal Highway Administration of the United States, the Surrogate Safety Assessment Model (SSAM) (Gettman *et al.*, 2008; Huang *et al.*, 2013; Morando, Truong and Vu, 2017; Katrakazas, Quddus and Chen, 2018; Rahman *et al.*, 2019a).

VISSIM is able to produce binary trajectory files which contain the information about the trajectory followed by every vehicle during a single simulation run. The user needs to select the corresponding SSAM option within the graphical user interface of SSAM. The data contained in the trajectory file are raw (unprocessed) and contain information about the geographical location of all vehicles at every simulation step along with vehicle kinematics data such as velocity, acceleration and heading (direction of movement). This trajectory file cannot be interpreted by a normal text editor as it is in binary form.

SSAM can read the trajectory files produced by VISSIM and calculates surrogate safety measures corresponding to each vehicle to vehicle interaction that it detects and determines whether the interaction satisfies the criteria to be categorised as an official conflict. The software uses two main threshold values for surrogate measures of safety to delineate which vehicle interactions are classified as conflicts; Time to Collision (TTC) and Post-encroachment time (PET). These two surrogate safety measures have been described in detail in section 3.4. The default threshold values of SSAM are 1.5 seconds for TTC which is suggested by existing literature for severe conflict situations (Lu, Pirinccioglu and Pernia, 2005; Li *et al.*, 2017a) and 5 seconds for PET which is originally suggested by (Hydén, 1987). The same threshold values were used in this thesis.

SSAM scans one simulation step at a time in order to identify vehicle interactions were these thresholds are violated. In addition to the thresholds, several algorithms are applied in order to confirm the occurrence of a conflict. Initially, SSAM divides the network area which is given by the first line of the trajectory file into a grid to cover the entire analysis area. Each square zone of the grid is 15.25 by 15.25 meters. By doing this, the software reduces considerably the number of vehicle to vehicle comparisons that are necessary to identify potential conflicts.

The next step is to analyse a single time step of the trajectory file. During this step, for each vehicle in the analysis area, SSAM projects the vehicle's expected location, at simulation time step intervals, as a function of its current velocity if it continues traveling along its future path for up to the duration of the calculated TTC value (see Figure 4.9). The vehicles path is discovered by SSAM by looking ahead over the next 10 seconds of trajectory data for this vehicle.

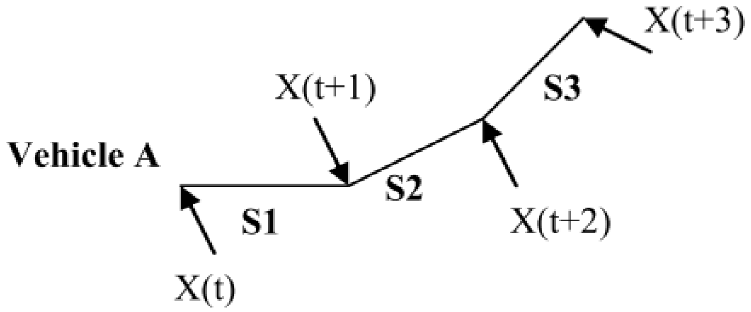


Figure 4.9 Illustration of projected vehicle path (Gettman *et al.*, 2008)

The exact process of the vehicle trajectory projection is taking place under the assumptions that;

a) each vehicle is defined as a rectangle
b) the distance that a vehicle will travel is calculated by using the maximum TTC value that was identified for the conflict under investigation according to equation (4.17), where V_1 is the speed of the vehicle under consideration

$$DIS_1 = V_1 * maxTTC \tag{4.17}$$

c) The location of the vehicle in the next time step (x_2,y_2) is calculated based on the distance from current location to that location according to equation (4.18) (see Figure 4.10)

$$DIS_2 = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (4.18)$$

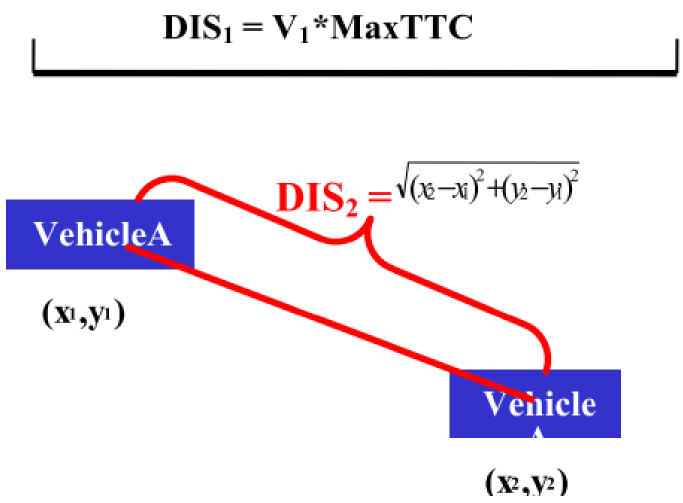


Figure 4.10 DIS1 and DIS2 according to SSAM (Gettman et al., 2008)

d) If DIS_2 is less than DIS_1 then DIS_2 is subtracted from DIS_1 and the previous two calculations are repeated with DIS_1=DIS_1-DIS_2

Last but not least, SSAM calculates the rectangular perimeter describing the location and heading of the vehicle at its projected future position. Then this rectangular area is placed on the grid that is described above in order to identify which zones of the grid at least some portion of the vehicle will occupy. Subsequently the vehicle is added to the “occupants” list of those areas. Any time a vehicle is added to an “occupant” list that currently contains one or more vehicles the software checks for potential vehicle overlap in order to identify a future collision. It is possible that due to the dimensions of the grid zones two vehicles may partially occupy the same zone without overlapping. However, two overlapping vehicles indicate clearly that a future collision is detected for this pair of vehicles and therefore a potential conflict is identified.

Using the process above, SSAM gathers all conflicts detected in a table and computes and records several variables for each conflict. These variables contain measures such as the TTC and PET for the conflict, the time that the minimum TTC and PET occurred, speeds and acceleration or deceleration rates of the participating vehicles at the minimum TTC time, identification number and heading of the conflicting vehicles, number of link (road) and lane where the conflict occured, exact geographical location of the conflict and finally the conflict angle as presented in Figure 4.11 as well as the conflict type.

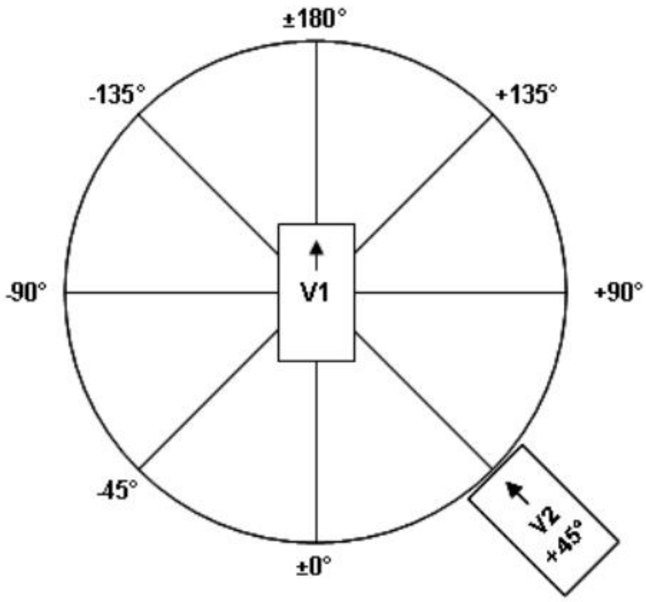


Figure 4.11 Conflict angle as perceived by SSAM (Gettman *et al.*, 2008)

More specifically, the conflict type variable describes whether the conflict is a rear-end, lane changing or crossing event. For this thesis, only lane changing and rear-end conflicts are considered since the evaluated road network is a motorway. The type of conflict is identified by SSAM using the angle of the conflict. A conflict is classified as rear-end if $|ConflictAngle| < 30°$, a crossing conflict if $|ConflictAngle| > 85°$, else it is classified as a lane changing conflict. The microsimulation software in most cases can provide lane and link information as well as lane changing information for both vehicles which can help identify the type of the conflict directly. For example, if a vehicle at the start of the conflict event is driving in a certain lane and at the end of the conflict even it is driving in a different lane the conflict is classified as a lane-changing conflict.

Finally, in order to facilitate the description of the conflict count statistical modelling, the formulation of the traffic conflict dataset is described below; Once SSAM calculates the number of conflicts per simulation run, the conflicts in this thesis are grouped according to their geographical location. The geographical location is delineated by the coordinates of where the minimum TTC is documented for the conflict. Afterwards, the locations of the conflicts are assigned to specific segments of the simulated motorway environment. The segments are defined by two consecutive data collection points in PTV VISSIM (see Figure 4.12) which operate identically to inductive loop detectors, collecting vehicle-level traffic data measurements such as speed, acceleration, occupancy and flow. The data from these simulation data collection points were combined with the corresponding number of conflicts hence a dataset was created where one observation contained information about the identification number of the segment, the corresponding number of conflicts which occurred in the 15 runs of the simulation, the CAV market penetration rate, the traffic flow of the segment, the standard deviation of speeds between lanes and within the same lane, the curvature of the segment counted as spinal points in the simulation etc. The flowchart of the formulation process of the traffic conflict dataset is presented in Figure 4.13. The dataset is described in section 5.4 in detail.

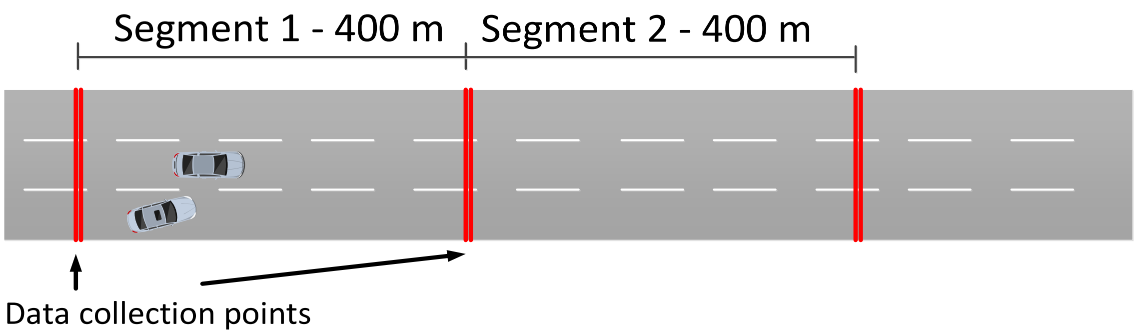


Figure 4.12 Data collection points and segments to facilitate traffic conflict analysis

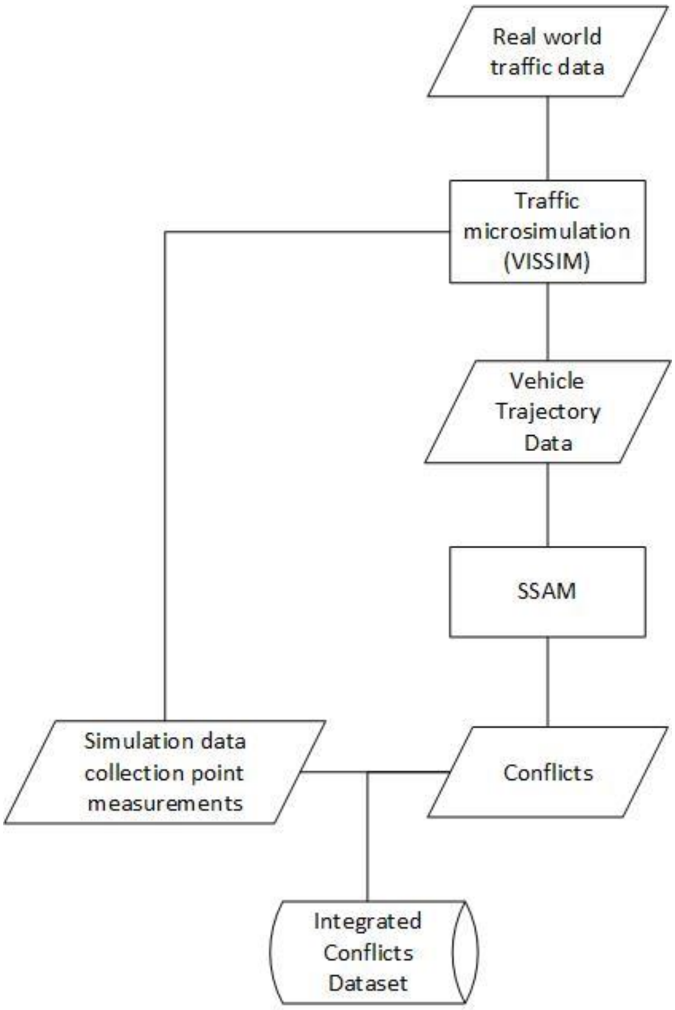


Figure 4.13 Flowchart of the conflict dataset formulation process

4.3.3 Statistical modelling

Modelling conflicts is a task that one can relate to modelling accidents which has been widely applied in existing literature (Lord and Mannering, 2010; Imprialou *et al.*, 2016). Traffic conflicts are discrete events that happen in a motorway and similarly to accidents, they are non-negative integer values. This type of data is widely known as count data and they are characterised by low mean values and heteroscedasticity. Their distributions usually are positively skewed and are kurtotic. Hence, the most common statistical approaches such as Ordinary Linear Regression models are often not appropriate for their modelling as the nature of the data may violate the underlying assumptions of the model regarding biased residuals. This consequently can lead to misleading results and more specifically, can paradoxically lead to the calculation of negative predicted values. The following sections describe the statistical models that were employed for the statistical analysis part of the thesis.

4.3.1.4. Negative binomial regression models

In order to tackle the aforementioned shortcomings such as the low mean values, negative binomial regression is used in this thesis. Negative binomial regression is similar to ordinary linear regression except that the dependent variable (Y) (in this case the number of conflicts) is an observed count that follows the negative binomial distribution $Y \sim NB(r, p)$ (Hilbe, 2012). The negative binomial distribution is also known as a generalisation of the Poisson distribution by including a Gamma (Γ(n) = (n-1)!) noise variable which has a mean of 1 and a scale parameter of v. This mixture is the only way in which the negative binomial probability distribution function can be defined. The probability distribution function of the negative binomial distribution is given by equation (4.19) however it can be found in several forms:

$$f(y|\mu, \alpha) = \frac{(y_i + \frac{1}{a})!}{y_i! \left(\frac{1}{a-1}\right)!} * \left(\frac{1}{1 + a\mu_i}\right)^{\frac{1}{a}} * \left(\frac{a\mu_i}{1 + \alpha\mu_\iota}\right)^{y_i} \qquad (4.19)$$

Where y is the dependent variable, α=1/r the negative binomial heterogeneity or overdispersion parameter, $\mu_i = t_i * \mu$ where μ is the mean incident rate of y per unit of exposure t_i. Exposure may be time, space, distance, area, volume or population size. In this thesis, traffic flow of each segment will be considered as the exposure variable.

In the negative binomial regression, the mean of y is determined by the exposure rate and a set of explanatory variables. The expression relating the quantities is:

$$\mu_\iota = \exp\left(\ln(t_i) + \beta_1 * \chi_{1\iota} + \beta_2 * \chi_{2\iota} + \cdots + \beta_n * \chi_{n\iota}\right) \qquad (4.20)$$

Often, $\chi_1 \equiv 1$ in which case β_1 is called the intercept. The regression coefficients $\beta_1, \beta_2, \ldots, \beta_n$ are unknown and are estimated from the data set. They can be estimated either with a frequentist approach using the maximum likelihood estimation (MLE) method or with a Bayesian approach using the Markov Chains Monte Carlo (MCMC) algorithm.

Negative binomial regression has been used in the literature to model accidents widely (Kim and Washington, 2006; Daniels *et al.*, 2010; Shankar, Mannering and Barfield, 2013). However, it has been proven to be problematic when the data used for its calculation has an excess number of zeros.

4.3.1.5. Hierarchical models

Many kinds of data have a hierarchical, nested or clustered structure. The most common example given in the literature for hierarchically structured data is a dataset containing the grades of students within a geographic region that belong to different schools. It is observed that there are similarities in the grade of students coming from the same school. To generalise, this means that similarities can be observed in data belonging to the same group which is formally called a level. In the example given above, the student observations can be called level 1 and the schools can be called level 2. Hierarchical data can contain more than 2 levels, however, the most common structure is a 2 level structure (Goldstein, 2011). A 2-level model is used for this thesis, hence the following paragraphs describe the formulation of the 2-level model.

Data that have a hierarchical structure can be modelled using hierarchical models (also known as multilevel models, mixed models or random-effect models). Hierarchical models are statistical models whose parameters vary at more than one level. The level 1 equation of a two level linear hierarchical model is presented below (Goldstein, 2011):

$$Y_{ij} = \beta_{0j} + \beta_{1j}\chi_{ij} + e_{ij} \qquad e_{ij} \sim N(0, \sigma_e^2) \tag{4.21}$$

- where i indicates the individual case, j the group,
- Y_{ij} refers to the score on the dependent variable for an individual observation at level1
- β_{0j} the intercept of the dependent variable in group j
- β_{1j} the slope coefficient for the relationship in group j between the level 1 predictor and the dependent variable
- e_{ij} the random errors of prediction for the level 1 equation

The level two equations of the statistical model of are derived by letting β_{0j} and β_{1j} become random variables. Therefore:

$$\beta_{0j} = \beta_0 + u_{0j} \tag{4.22}$$

$$\beta_{1j} = \beta_1 + u_{1j} \tag{4.23}$$

Where u_{0j} and u_{1j} are now random variables with parameters:

$E(u_{0j}) = E(u_{1j}) = 0$ and $var(u_{0j}) = \sigma_{u0}^2$, $var(u_{1j}) = \sigma_{u1}^2$, $cov(u_{0j}, u_{1j}) = \sigma_{u01}$,

By using equations (4.22) and (4.23) equation (4.21) can be re-written as:

$$Y_{ij} = \beta_0 + \beta_{1j}\chi_{ij} + (u_{0j} + u_{1j}x_{ij} + e_{0ij}) \tag{4.24}$$

Equation (32) expresses the dependent variable Y_{ij} as the sum of a fixed part and random part (within the brackets).

Before performing a multilevel model analysis, several decisions must be made. Initially one must decide on which explanatory independent variables are going to be included in the analysis and secondly, whether the parameters of the independent variables are going to be fixed or random (Goldstein, 2011). Fixed parameters are considered to be constant across all groups of the dependent variable whereas random parameters have a different value for each of the groups.

There are three types of hierarchical models, namely random intercepts, random slopes and random intercepts and slopes model. In random intercept model is a model where only the intercepts (u_{0j} in equation (32)) are allowed to vary across groups and therefore the calculation of the dependent variable happens by the intercept that correspond to each group. In this type of model, the slopes are fixed. Random slopes model is a model in which slopes are allowed to vary, and therefore the slopes are different across groups. The intercepts are not allowed to vary in this type of model. Finally, random slopes and intercept model is a model where both intercepts and slopes are allowed to vary across groups. Likely, this type of model is the most realistic model (Goldstein, 2011).

In order for the best model to be identified one should first attempt to identify the presence of similarities among observations of the same groups. One method to do that is by applying the Intraclass Correlation Coefficient (ICC) which measures the correlation between observations within a given cluster. The equation of the ICC is given below.

$$ICC = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2} \tag{4.25}$$

where σ_u is the variance of the observations between different groups and σ_e the variance of the observations between the same group. Finally, in order to identify whether the random effect is significant or not the chi-squared likelihood ratio test which assesses the difference between models can be applied. The likelihood ratio test can be used for model building when examining models in which effects are allowed to vary. The statistics of the likelihood ratio test is described in equation (4.26) where LL are the loglikelihood values of the models that are being compared.

$$LR = 2 \times (LL1 - \mathrm{LL2}) \tag{4.26}$$

where LL1 and LL1 are the loglikelihood values of the two compared models.The null hypothesis of the test is that there are no significant differences in the two models that are being compared and hence the alternative hypothesis is the opposite. The value calculated by equation (4.26) is compared with a value obtained from the chi-squared distribution table with degrees of freedom equal to the number of extra parameters included in the more complex model.

The data in this thesis are organised in 2 levels as the ICC calculation (0.88) indicated that there are similarities in conflicts arising from the same segment. Namely, the first level includes the CAV market penetration rate and the second level includes the segment identification number. This hierarchy was decided by observing the ICC coefficient described above and using common sense. In this manner, it is assumed that there are similarities in the conflicts number arising from the same segment. Finally, because of the reasons described in section 4.3.1.4, a negative binomial regression model is used in combination with the multilevel model. The final equation of random slope and intercept negative binomial model is presented in equation (4.27) by combining equations (4.20) and (4.24).

$$\ln\,(\mu_{ij}) = \ln(t_i) + (\,\beta_0 + \beta_{1j}\chi_{ij} + (u_{0j} + \,u_{1j}x_{ij} + e_{0ij})) \tag{4.27}$$

4.3.1.6. Spatial correlation

In all the models presented in the two previous sections it is assumed that the observations of the dependent variable are spatially independent. To put some context, a similar assumption to this study would be that the traffic conflict count of a particular segment of the motorway is independent of the traffic conflict count of neighbouring segments. However, this statement might be incorrect hence, further investigation is needed.

This issue is widely known as spatial autocorrelation and a number of studies have emphasized the importance of including a spatial autoregressive model into the analysis when analysing spatial data (Quddus, 2008; Lord and Mannering, 2010; Washington, Karlaftis and Mannering, 2010; Imprialou *et al.*, 2016). The formulation of the equation of a traditional econometric spatial autoregressive model is given below:

$$Z_i = \rho W Z_i + \beta X_i + \varepsilon_i \tag{4.28}$$

where Z is a N x 1 vector of cross-sectional dependent variable, WZ is a spatially lagged dependent variable for spatial weights matrix W, ρ the scalar for spatial lag coefficient, β is the vector of parameters to be estimated, X is the matrix of explanatory variables and ε is a N x 1 vector of a normally distributed error terms with zero mean and variance σ^2. The spatial lag WZ can be considered as a spatially weighted average of the dependent variable at neighbouring spatial units.

The aforementioned model does not excel at modelling non-negative count data. Hence, in order to combine the spatial autoregressive model with the two aforementioned models (negative binomial and hierarchical) a Bayesian approach using the Markov Chain Monte Carlo (MCMC) method (Gelman *et al.*, 2013) is used. Bayesian analysis differs from traditional frequentist statistical approach mainly due to the estimation method used to calculate the coefficients. In Bayesian analysis, the coefficients are assumed to follow a distribution which is based on prior knowledge. This prior knowledge is the basis for the start of the calculation of the coefficients of the model until the model converges to the “real” values of the coefficients using the MCMC method. Spatial autocorrelation is often accompanied by uncorrelated random effects which are caused due to unobserved heterogeneity in the dataset. The formulation of a Bayesian hierarchical negative binomial model is presented below (Besag, 1974; Quddus, 2008):

$$\ln(\mu_i) = \ln(t_i) + (b_0 + bX_i) + SC_i + UH_i \quad \textbf{(4.29)}$$

$$Y_i \sim NB(r, p) \quad \textbf{(4.30)}$$

$$\mu = \frac{r(1-p)}{p} \quad \textbf{(4.31)}$$

where r,p are the parameters of the negative binomial distribution, SC_i the random spatial effects, UH_i the unobserved heterogeneity (uncorrelated random effects). In equation (4.29) the prior distributions for b_0 and b’s and UH can be set according to guidelines found Quddus, (2013). All b’s follow a highly non-informative normal distribution with zero mean and UH is assumed to follow a normal distribution N(0,τ_{UH}^2) where τ is the precision (i.e. 1/variance) with a prior gamma distribution Ga(0.5, 0.0005). The effect of spatial correlation is included as a conditional auto-regressive prior (CAR) with N($\overline{S_\iota}$,τ_i^2) with $\overline{S_\iota}$,τ_i^2 being defined by the following equations:

$$\overline{S_\iota} = \frac{\sum_j SC_j w_{ij}}{\sum_j w_{ij}} \quad \textbf{(4.32)}$$

$$\tau_i^2 = \frac{t_{sc}^2}{\sum_h w_{ij}} \quad \textbf{(4.33)}$$

With w being defined above and t_{sc}^2 assumed to follow a gamma prior distribution with Ga (0.5, 0.0005).

It must be emphasized that even though spatial autocorrelation is a realistic usual potential issue when dealing with accident or conflict data, its appropriateness though for this thesis needs to be examined thoroughly. In order to do this, the Moran’s I statistical test is employed, which tests the presence of spatial correlation in the dataset. The formulation of the equation of the Moran’s I statistic which will decide the presence of spatial autocorrelation in the dataset is described in the corresponding statistical results section. In order to evaluate the fit of the models developed, the goodness of fit statistic Deviance Information Criterion is employed which is used to compare the fit of models estimated on a full Bayesian inference approach. The best fitting model is the most parsimonious – a model that accomplishes a good level of explanation of the data using the least explanatory variables possible. This model will have the smallest DIC value among all the possible models (Spiegelhalter, Best and Carlin, 2002). The mathematical formulation describing the DIC is presented below:

$$DIC = D(\bar{\theta}) + 2p_D = \bar{D} + p_D \tag{4.34}$$

Where $D(\bar{\theta})$ is the deviance of the θ posterior means of the model parameters, p_D the effective number of parameters in the model and $\bar{D}$ the posterior mean of the deviance, $D(\bar{\theta})$.

4.4 Summary

This chapter initially presented the objectives of this thesis and the corresponding chapters of the thesis which address them. Subsequently, the algorithmic, statistical and simulation methods employed in the thesis in order to address the aforementioned objectives were presented.

The traffic microsimulation section of this chapter presented the major elements that were the main actors of the simulation framework that is developed. More specifically, the human driving behaviour according to VISSIM was described in depth in order to obtain a wider understanding and facilitate the interpretation of the CAV-human driven vehicle interactions. Following, the developed CAV control algorithm was described for the first time in this section. More specifically, the functionality of the API which was developed was presented with relation to the subsystems which rule the operation of a real-world CAV. Following, this section also presented the scenarios that were tested in this thesis which were various traffic flow scenarios, vehicle platoon size scenarios, sensor error rate scenarios, and scenarios investigating the effectiveness of the route-based decision-making CAV algorithm.

Afterwards, the functionality of the post-processing conflict identification software SSAM was described alongside with the algorithms that control the process. In order to obtain a wider understanding of the challenges arising from the traffic conflict dataset which was analysed in the next section, the flowchart of the formulation of the traffic conflict dataset was described.

Last but not least, the statistical models that were employed in order to model the traffic conflict dataset were presented. In summary, most accident and consequently conflict datasets are modelled using negative binomial regression due to low sample means. In order to take into account similarities arising from the occurrence of traffic conflicts within the same section of the motorway, multi-level statistical modelling was described. Finally, the use of a spatial autocorrelation term to account for similarities in the occurrence of traffic conflicts between neighbouring motorway sections was presented. The overall methodological flowchart described in this chapter is presented below:

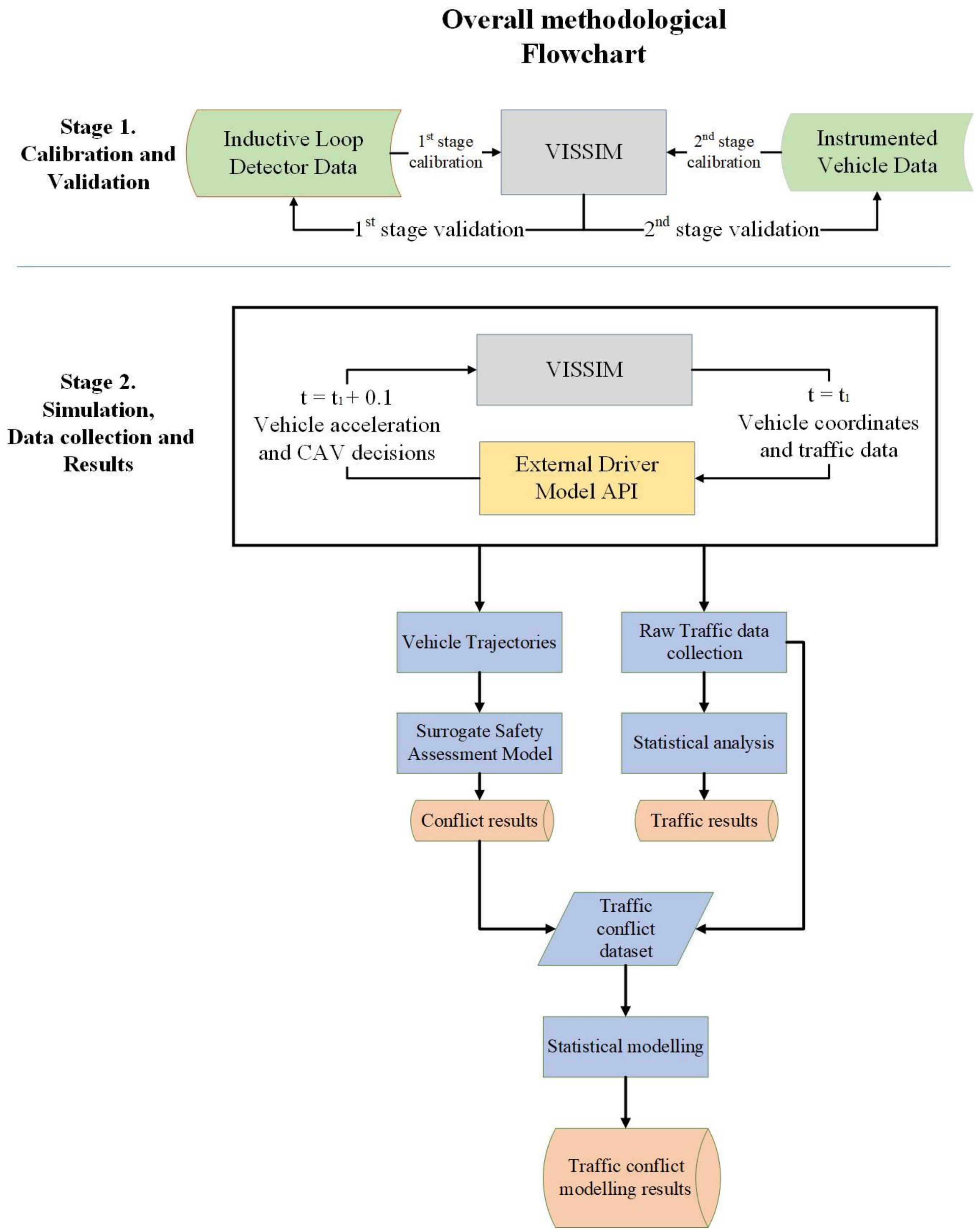


Figure 4.14 Overall methodological flowchart followed in the present thesis

5 Data description and Pre-processing

In order for traffic microsimulation to provide a reliable result, a calibration and validation process is required. Section 4.3.1.2 underlined that the calibration and validation of a traffic microsimulation model relies on real-world data which are compared with corresponding simulated data. This comparison results on the alteration of the parameters of the simulation model in order for the simulated data to be as close as possible to the real-world data. The real-world motorway and naturalistic driving radar data used for this thesis are presented in this chapter. Following, the motorway study area is presented.

Finally, this chapter provides a detailed description of the traffic conflict data set which is created for statistical modelling purposes. The flowchart of the formulation of this dataset was presented in section 4.3.2.

5.1 Study Area

This PhD focuses on assessing the safety impact of CAVs on motorways and the developed CAV driving model as well as the human driver model are developed and selected accordingly based on this focus. A section of the M1 motorway is chosen as a testbed to apply the aforementioned models. The M1 motorway is part of the Strategic Road Network (SRN) which is operated by the government-owned company Highways England. The entire M1 motorway connects London to Leeds in the United Kingdom. The total length of the M1 motorway is 193.5 miles. For the purpose of this thesis, a part of the M1 motorway between junctions 21 and 19 were selected as a study area. Junction 21 of the M1 motorway is located southwest of Leicester and Junction 19 is located southeast of Rugby in the United Kingdom. The GPS coordinates for junctions 21 and 19 are (52°36'01.2"N 1°11'41.9"W) and (52°24'16.3"N 1°10'36.1"W) accordingly. The study area is shown in Figure 5.1.

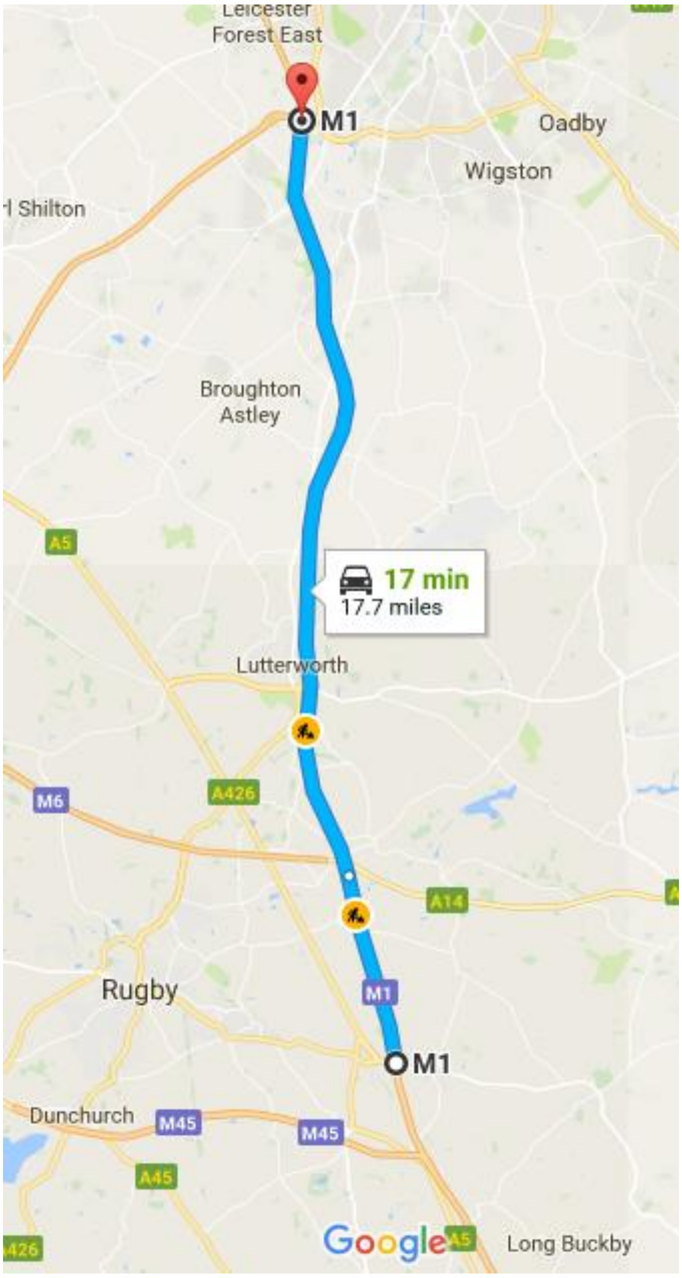


Figure 5.1 Motorway network study area

Several reasons led to the choice of this specific segment:

- **Constant number of lanes:** In order to avoid possible bugs and problems in the simulation software related to changes in the number of simulated lanes, the number of lanes of the segment chosen was decided to be constant. The selected segment of M1 between junctions 19 and 21 contained 3 lanes throughout its whole length;

- **Location:** The selected section was close to Loughborough University were this PhD thesis was written. Since the required traffic and safety surrogate measure data have to be gathered frequently, this specific segment of M1 was a convenient location due to the proximity to the University;
- **Availability of historical data:** Historical, minute-level traffic data including average speed, headway, traffic flow and occupancy were available for this specific segment and no faulty inductive loop detectors were identified;
- **Favourable traffic conditions:** The segment of the M1 chosen, had a stable Annual Average Daily Traffic flow during the simulation times (11:00-12:00 a.m.);
- **Stable pavement condition:** No roadworks was conducted in the selected road segments during the data collection periods (May 2017 – source: Highways England);
- **Stable safety performance:** After exploring and mining STATS19 accident data from the UK Department for Transport, it was proven that the number of accidents happening in the selected road segments remained relatively constant during the period 2012 to 2014 (see Table 5.1).

Table 5.1 Number of accidents per year in the selected M1 segment (source: Department for Transport Stats 19 data)

Year	Number of accidents	Accident Severity 1	Accident Severity 2	Accident Severity 3
2012	32	0	3	29
2013	31	1	1	29
2014	27	2	3	22

Initially, by using an aerial photograph provided by VISSIM, both directions Northbound and Southbound of the road network were drawn. Lane width was set to represent the real-world measurement (3.5 meters) and the length of links, merging and diverging areas were drawn according to the aerial photograph (see Figure 5.2). More specifically, the merging and diverging areas were designed following guidelines from literature specialising in motorway merge areas (e.g. (Fan *et al.*, 2013; Whaley, 2016)). Figure 5.3 presents a more detailed picture of the merging/diverging area at junction 19 versus how it appears in the real world. The total length of the mainline corridor designed was 44.27 km, contained eight on and off-ramps in total and six vehicle input points. The model designed, did not contain the roundabout at Junction 20.

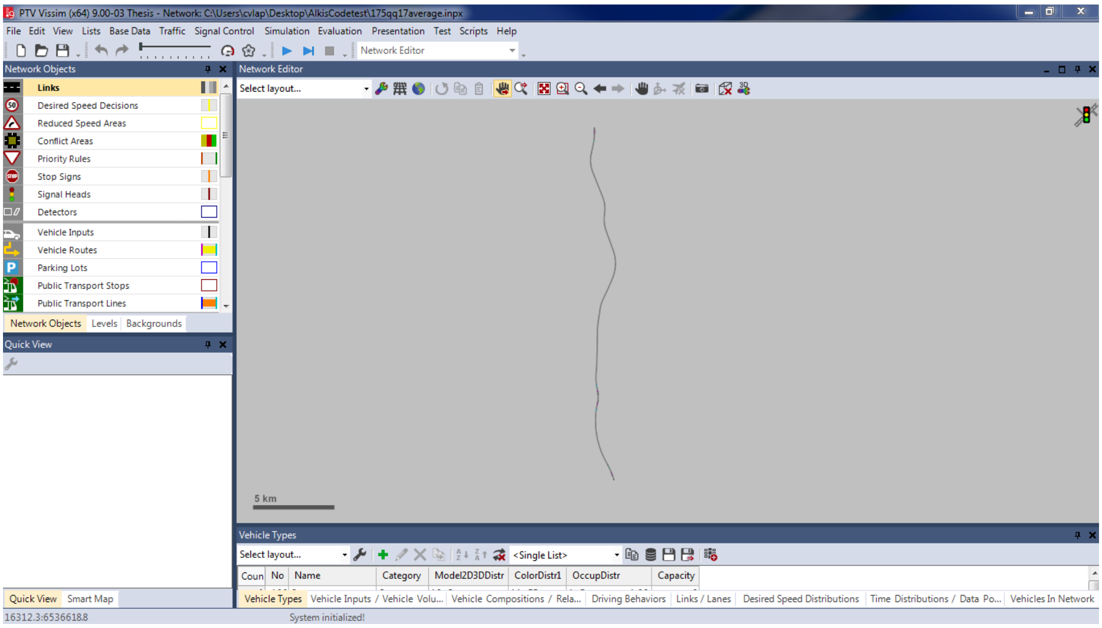


Figure 5.2 The motorway study area as it appeared in the simulation software VISSIM

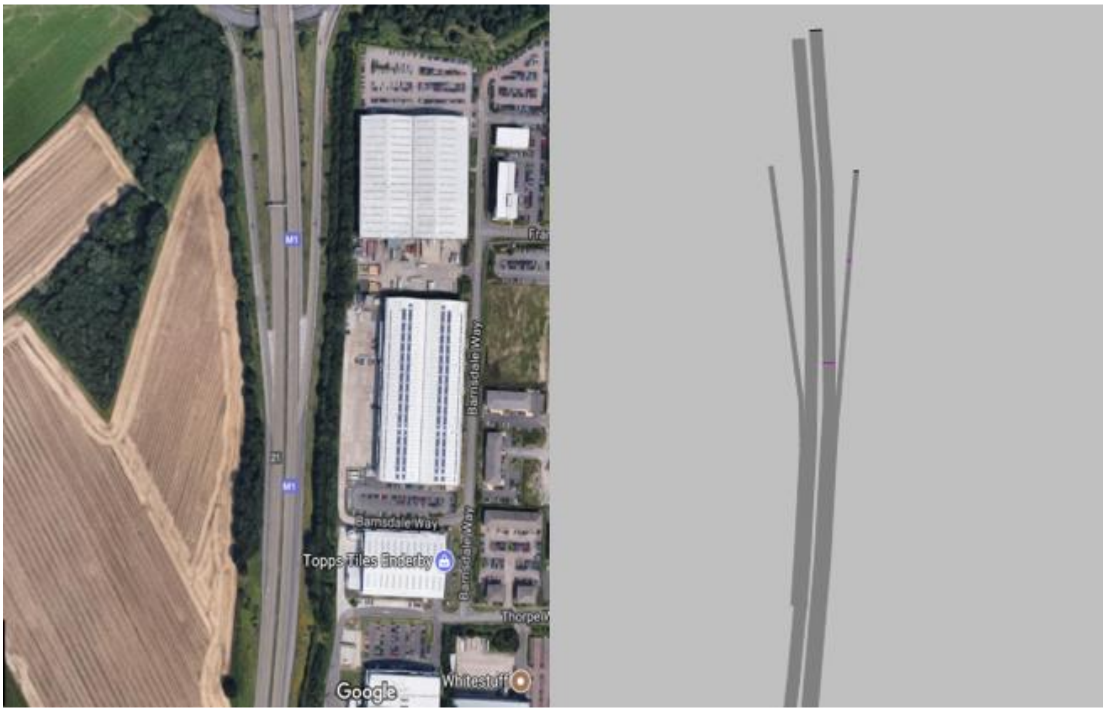


Figure 5.3 A detail of a merging/diverging area of the simulated network

The company responsible for the operation of the M1 motorway has installed several inductive loop detectors (IDL) along the segment of the motorway. These inductive loop detectors are installed at regular space intervals of approximately 400 to 500m and they record traffic data. The outline of the network along with its main elements as it appeared in VISSIM is presented below:

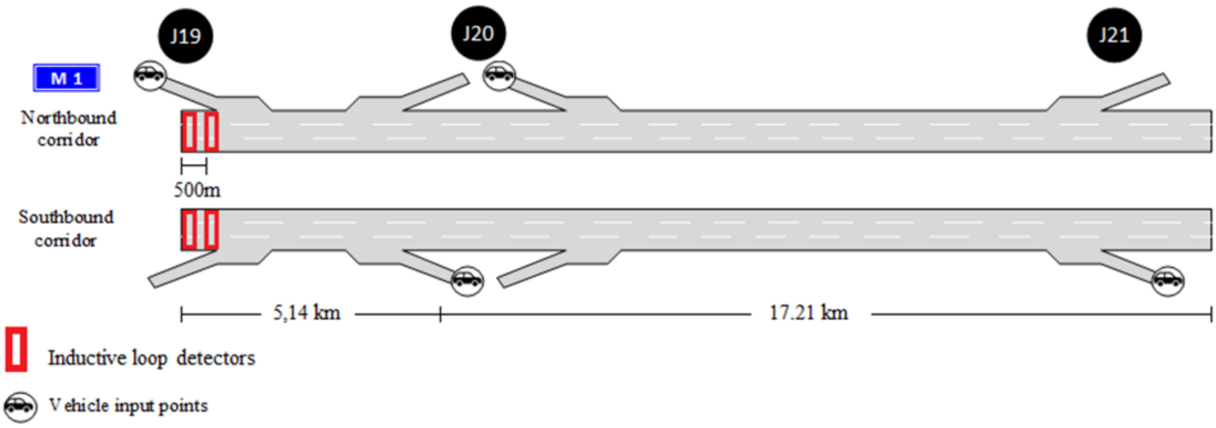


Figure 5.4 Outline of the simulated motorway segment

5.1.1 Limitations of the study area

Even though the simulated network is drawn in the traffic microsimulation software with the assistance of an aerial photo and following guidelines for literature which specialises in simulation network design, it will always be a simulated network which cannot replace or represent the real network one hundred percent.

Additionally, the study area included a section of the M1 motorway which had a constant number of lanes throughout the whole length. Even though this was selected for simplification and programming purposes, the effect of the sudden change in the number of lanes in the motorway could be an interesting research topic.

Finally, even though the study area contained 3 junctions it must be emphasized that no motorway weaving sections (a section of the motorway with length of 100 to 3000 meters connecting a pair of closely spaced junctions) neither the corresponding roundabout of Junction 20 which connects the merging and diverging areas were modelled in this thesis.

5.2 Data from Inductive Loop Detectors

Secondary inductive loop detector data are used for this study. An inductive loop detector is an electromagnetic detection system which uses a magnet to induce an electric current in a nearby wire. These detectors are installed in the pavement on the motorway and using the aforementioned process, they identify vehicle passages. Every time a vehicle is detected a measurement is recorded. Subsequently, the raw gathered data are aggregated to a minute-level detail. The traffic data are obtained through the HATRIS (Highways Agency Traffic Information System) which is the main database of traffic data in the UK. The original purpose of this data is to detect disturbances in the motorway traffic flow to enhance signalling, hence, they can be found with the name MIDAS (motorway incident detection and signalling). A list of the variables that the raw dataset contains is presented in Table 5.2.

Table 5.2 Meta data for the inductive loop detector data

Variable name	Description
geographicaddress	Name of the inductive loop detector
date	Date of the observation
time	Time of the observation (minute level)
numberoflanes	number of lanes at the position of the loop detector
flowcategorylane#	traffic flow in each lane per vehicle category (veh)
speedlane#	average speed of the vehicles that passed by the inductive loop detector during the time period (km/hour)
flowlane#	traffic flow per lane (veh)
occupancylane#	average occupancy of the inductive loop detector per lane (%)
headwaylane#	average headway of the vehicles within the time period (m)

In this PhD thesis the purpose of this data is to perform the first stage of the calibration and validation process of the baseline traffic microsimulation models that are developed. The term baseline will be used from this point on to describe the 0% CAV market penetration scenario, meaning the situation when the motorway is occupied by only human driven vehicles. Due to limitations in data availability for the second stage calibration process, the baseline traffic microsimulation model (scenarios 1, 6, 11, 16, 21 which were the baseline scenarios for the weekdays between Monday to Friday) are calibrated and validated for the time period between 11:00 and 12 a.m. Hence, the raw data are filtered by time, keeping observations between 11:00 and 12:00 a.m and subsequently by location, keeping only the inductive loop detector data for the simulated motorway network.

Initially, as the data are downloaded into separate files containing one day's worth of data, all the data files are merged together. The data files contain traffic data from January 2016 and February 2017. This initial dataset is split into a calibration dataset containing data from January 2016 to December 2016 and a validation dataset January 2017 to June 2017. Following, the raw IDL data are appropriately processed in order to achieve the following two objectives:

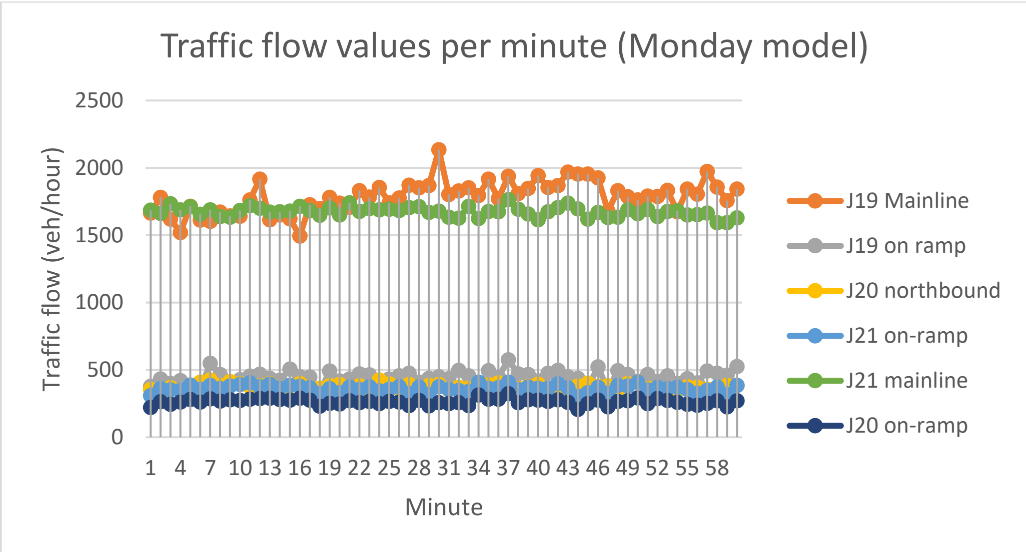
a) Form a simulation input dataset for the traffic microsimulation model that includes simulation speed distribution, simulation time headway distribution, traffic flow per minute, route choice percentages and fleet composition characteristics
b) Form a calibration and validation dataset containing traffic flow values

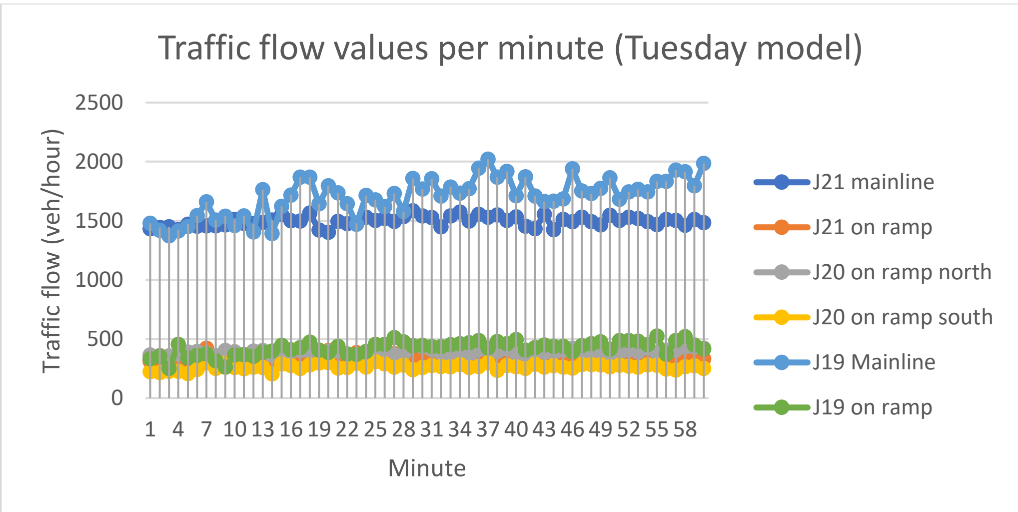
In order to achieve the first objective, data are collapsed by using the collapse command in the statistical software STATA which creates an average value by using a grouping variable. Hence the data are averaged by minute of observation in order to create a dataset which contains one observation per minute. The per-minute traffic flow values are presented in Figure 5.5. It must be underlined that the traffic flow values are calculated for the IDLs corresponding to the simulation vehicle input points (see Figure 5.4). The traffic flow values used in the baseline models are presented below where the standard deviation from the average traffic flow value is presented in brackets in order to represent the traffic flow differences per minute:

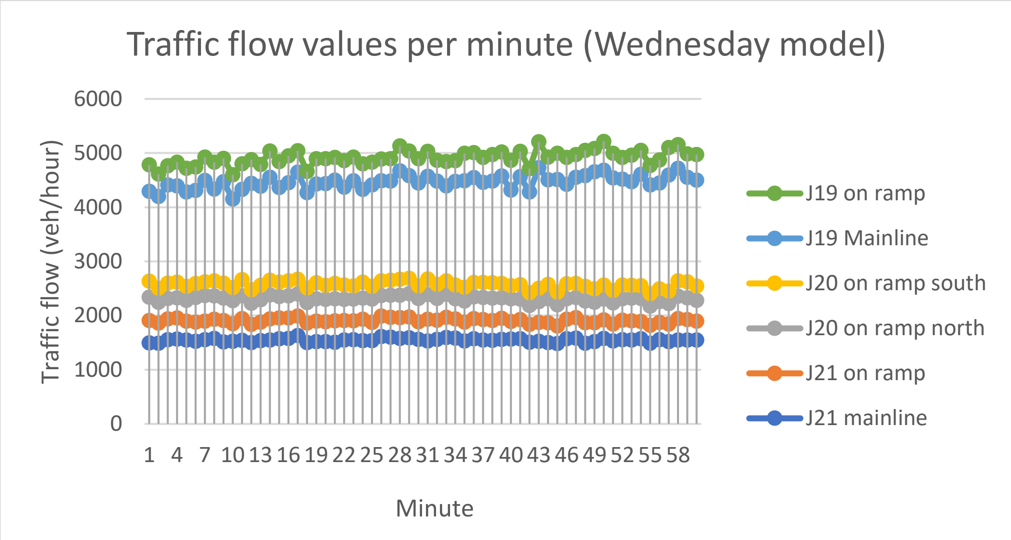
Table 5.3 Vehicle input point traffic flow in the baseline models

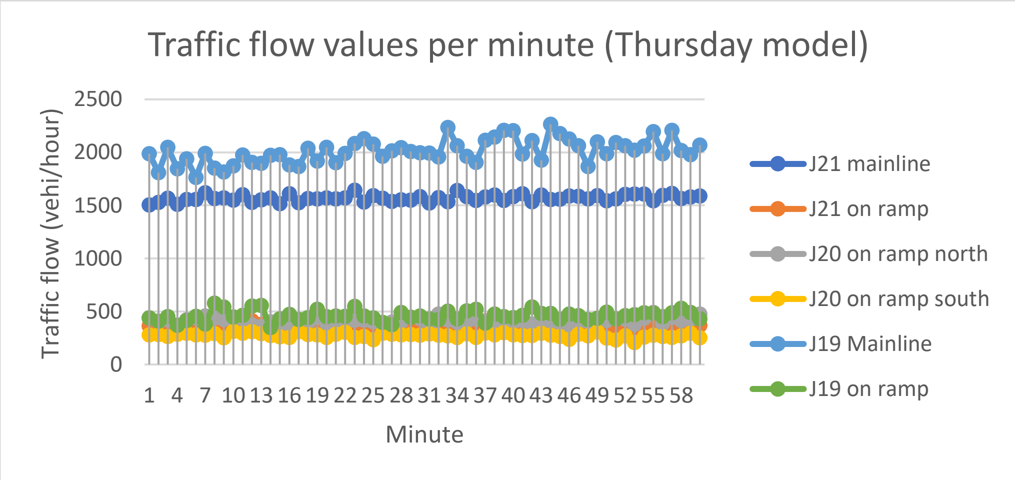
Vehicle input point	**Baseline Scenario (traffic flow value (standard deviation))**				
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
21 Southbound (main line)	1673 (35)	1495 (41)	1545 (32)	1568 (30)	1697 (36)

21 Southbound (on-ramp)	364 (24)	365 (26)	364 (20)	375 (25)	396 (25)
20 Northbound (on-ramp)	377 (20)	389 (22)	402 (24)	410 (28)	461 (24)
20 Southbound (on-ramp)	263 (21)	263 (22)	263 (19)	274 (20)	296 (21)
19 Northbound (main line)	1785 (119)	1706 (160)	1894 (129)	2011 (112)	2496 (177)
19 Northbound (on-ramp)	443 (49)	422 (56)	447 (39)	460 (47)	509 (52)









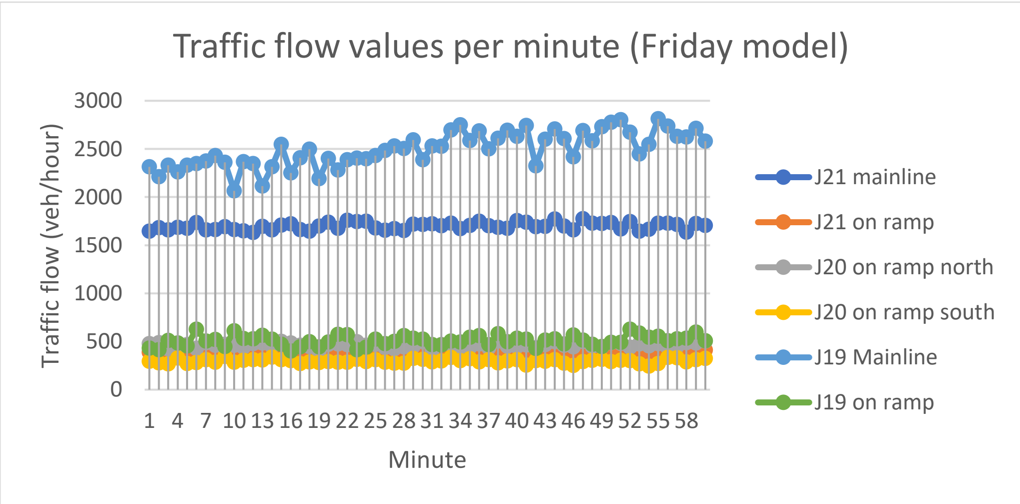


Figure 5.5 Temporal distribution of traffic flow in the simulation vehicle input points

Additionally, from these traffic flow values, the percentage of vehicles exiting the motorway was derived by identifying the corresponding IDL of the motorway and comparing with the flow upstream and downstream from it. This percentage was essential in order to program the route decision of vehicles in VISSIM. The corresponding percentages were assigned to the corresponding vehicle routes and the turning decisions of the vehicles in the simulation software. The results are presented in Table 5.4.

Table 5.4 Vehicle turning percentage in the exit ramps of the motorway study area

Exit ramp	**Baseline Scenario**				
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
21 Northbound	19.88%	19.72%	19.12%	18.63%	16.93%
20 Southbound	13.59%	14.99%	14.57%	14.89%	14.58%
20 Northbound	17.01%	18.17%	17.53%	16.93%	15.60%
19 Southbound	12.58%	13.06%	12.93%	13.01%	12.89%

Additionally, the dataset contained vehicle fleet composition information. As the percentage of heavy goods vehicles (HGVs) could not vary over the duration of the simulation the average value for the simulation time was calculated from the IDL data for each of the baseline traffic microsimulation models (see Table 5.5).

Table 5.5 Percentage of HGVs in the baseline traffic microsimulation models

Day of the Week	**Percentage of heavy good vehicles**
Monday	15.66%
Tuesday	14.63%
Wednesday	16.01%
Thursday	15.33%
Friday	14.55%

The minute level traffic flow data described above are used as input in each of the vehicle input points in order to accurately represent the traffic flow fluctuations of the corresponding weekday. The fleet composition and routing decision data are subsequently used as input for the simulation and the fleet composition and the routes with the corresponding percentages are defined in VISSIM.

The same aggregation procedure described above is followed for average speed and average time headway values. However, instead of per minute values, a statistical distribution is calculated. The distributions could not differ spatially in VISSIM within the same segment, so the headway and speed values per minute were averaged from all sensors and the derived distributions are presented in Figure 5.6 and Figure 5.7 accordingly. The average and standard deviation values of the aforementioned distributions are presented in Table 5.6. The speed measurements were input in VISSIM in the exact form of the cumulative speed distributions and the time headway distribution was input exactly in the form presented in Figure 5.6. An example can be seen in Figure 5.8.

Table 5.6 Descriptive statistics (mean and standard deviation) for IDL speed and time headway data

		Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Speed	Mean	110.27	109.37	108.88	108.09	105.56
	s.d.	12.62	13.14	13.09	12.91	11.72
Time Headway	Mean	1.64	1.74	1.70	1.62	1.37
	s.d.	0.07	0.08	0.10	0.10	0.16

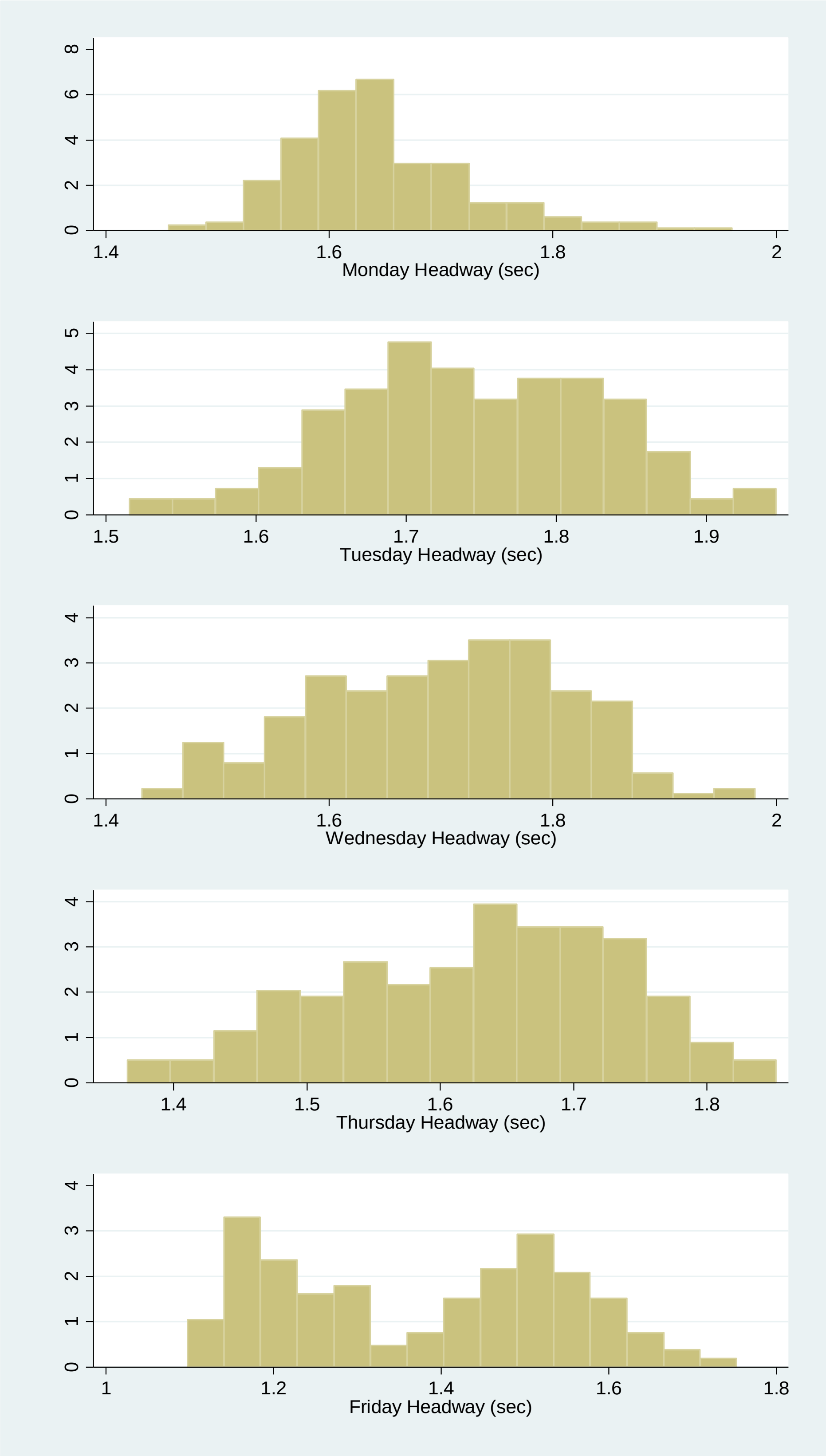


Figure 5.6 Time headway frequency distributions for the baseline weekday microsimulation models

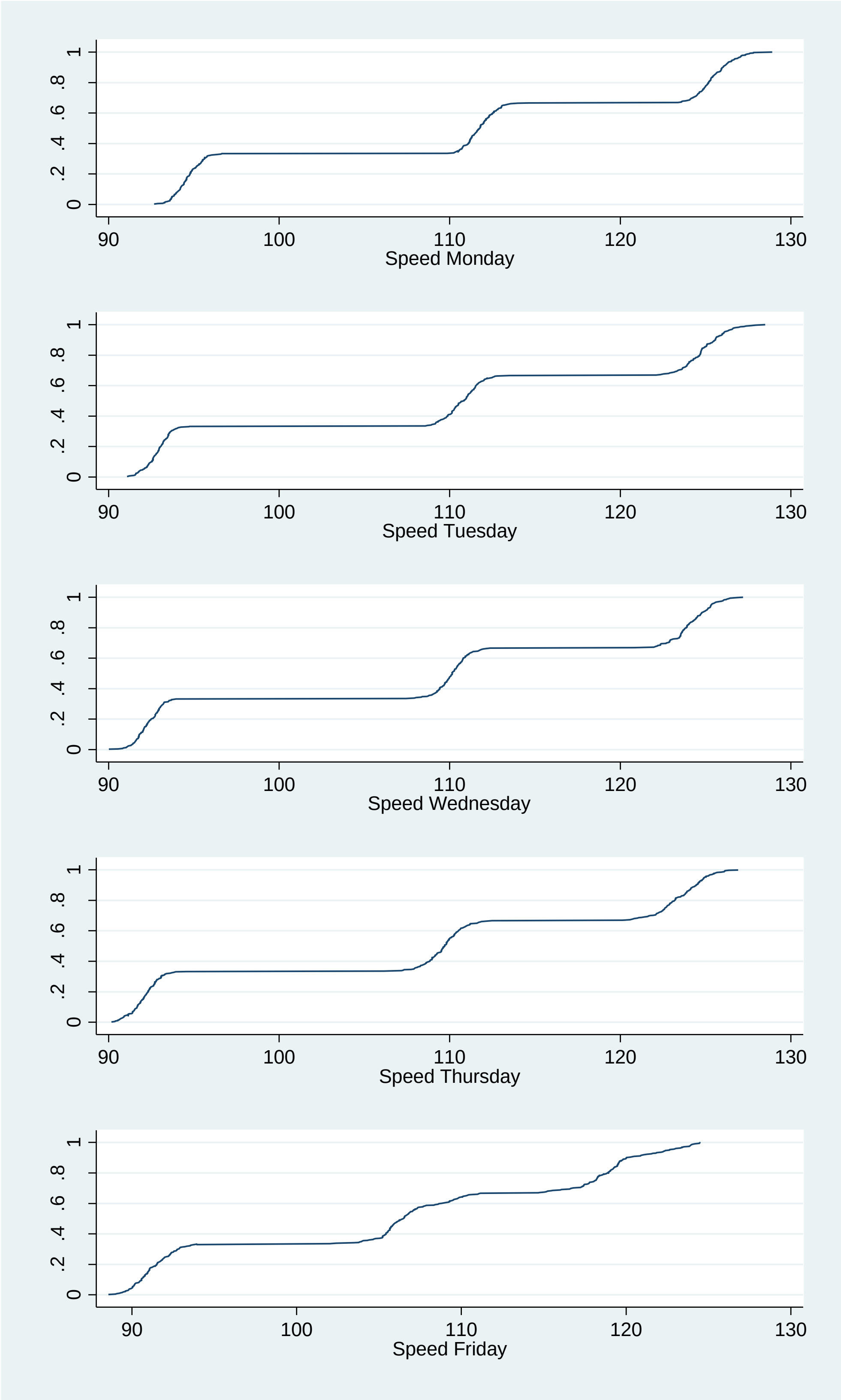


Figure 5.7 Cumulative speed distribution for the baseline weekday microsimulation models

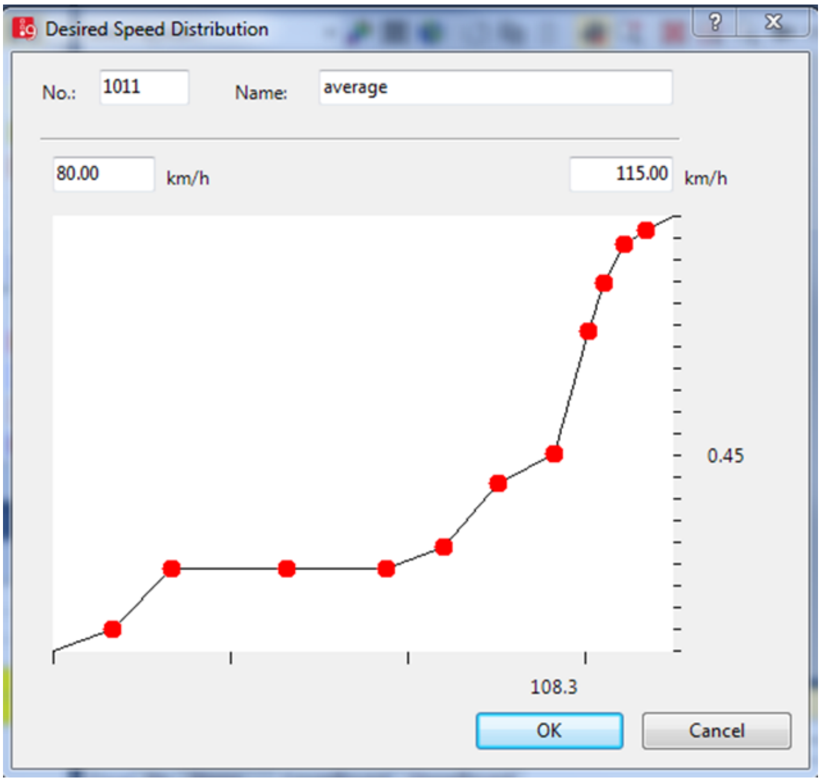


Figure 5.8 Cumulative speed distribution as seen in VISSIM

As mentioned above, the purpose of the aforementioned data was to perform the first stage calibration of the microsimulation models. The process followed for the first stage of the calibration process is described in section 4.3.1.2; Following guidelines provided by FHWA (Dowling, Skabardonis and Alexiadis, 2004), the measures of performance chosen for this stage of calibration are travel time and traffic flow values. According to these guidelines for travel time calibration, simulated values should be within a range of ± 15% of the observed values for more than 85% of the observation pairs.

The travel time for the real world is calculated as the product of the average speed derived from the real-world distribution and the distance travelled (mainline). The travel times of the simulated vehicles were gathered directly from VISSIM. The results of the calibration of the travel time values are presented in Figure 5.9. It is observed that the results of the travel time calibration did not require the adjustment of any driving behaviour parameters.

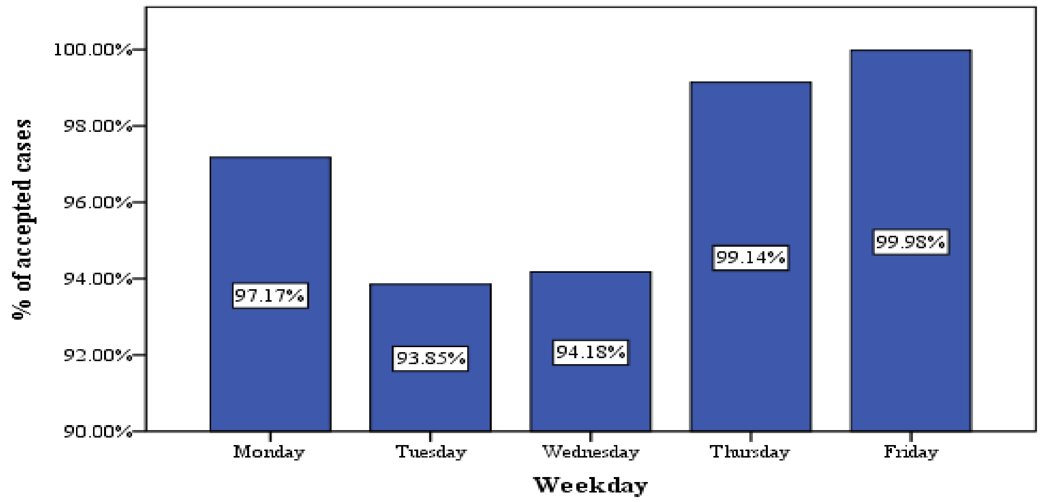


Figure 5.9 Travel time calibration results

On the other hand, in order to calibrate traffic volume values, the GEH statistic is used. The GEH statistic is presented in equation (4.9) . In order for the calibration process to be successful, the GEH statistic should be less than 5 for 85% of the observation pairs (simulated versus real world). The results of the calibration of the traffic flow values are presented in Figure 5.10 where the calculated GEH statistic value is compared with the threshold value of 5. As it is observed, all values were lower than 5, hence no adjustments are made to the default driving behaviour parameters of VISSIM.

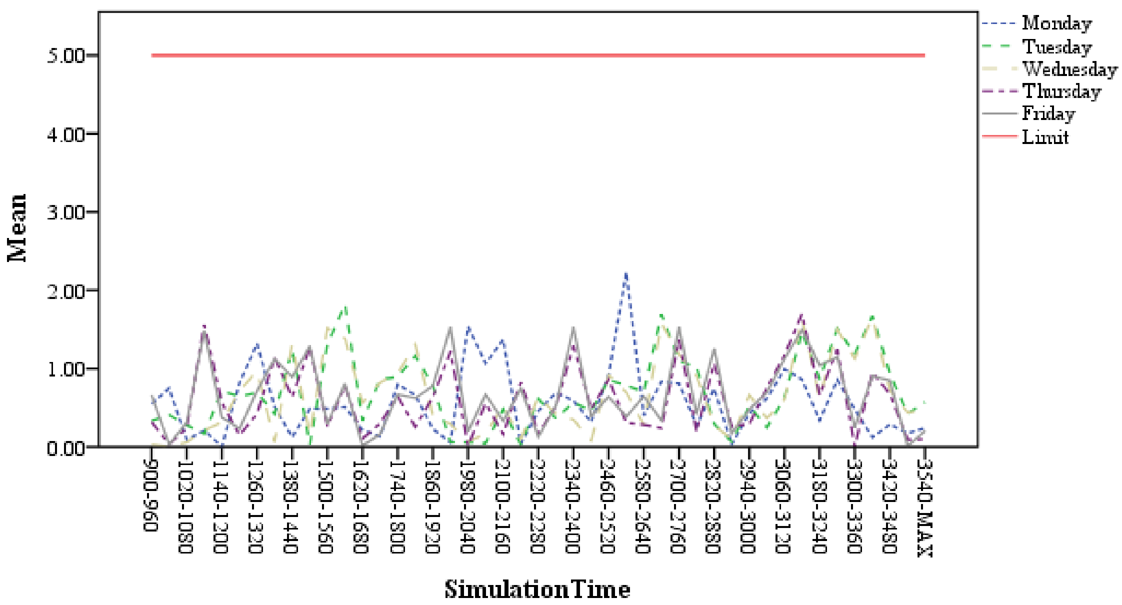


Figure 5.10 Traffic flow calibration results

Finally, the results of the calibration process were validated using the validation dataset using the same process.

5.2.1 Limitations of the inductive loop detector data

The highly disaggregated inductive loop detector dataset used in this thesis is one of the most detailed datasets found in existing literature. It is used as direct input to the baseline traffic microsimulation models and provides a solid foundation on which the first stage calibration and validation of the traffic microsimulation models is based. This dataset however was used to calibrate and validate only the human driving behaviour.

Additionally, as explained above, the values used as input are annual mean values of the traffic flow, speed, and time headway per minute of the simulation time (11:00 to 12 am). Hence, they cannot represent potential special conditions which may arise in a motorway due to an incident such as a lane closure.

Finally, the traffic flow values, and the speed distributions used in this thesis remained constant as the market penetration rate of CAVs increased. To elaborate, this means that the CAVs would eventually select their initial desired speed from the human desired speed, even though they would then adapt their speed according to the preceding vehicle and form platoons. This assumption is based on the fact that the speed of a vehicle in a motorway depends highly on the mechanical characteristics of the vehicle and these are assumed to stay the same for the purpose of this study for CAVs. Similarly, as far as traffic flow is concerned, even though literature have indicated that due to CAVs there might be induced traffic demand as a result of increased mobility needs during the CAV era, for the purpose of this study the traffic demand remained constant over the market penetration rate scenarios.

5.3 Data from Instrumented Vehicle

The second source of data used for this thesis is data collected using the instrumented vehicle of Loughborough University. The purpose of this data is to perform the second stage calibration and validation of the baseline microsimulation models. The exterior of the vehicle is shown in Figure 5.11 . This vehicle is equipped with a Continental ARS 308-21 long range radar , a PointGrey Grasshopper 3 (GS3-U3-41C6C-C) camera, a Ublox NEO-M8L GPFS (GNSS), a Mobileye device and data are communicated through different devices using a CANbus. Furthermore, a code written in C was developed on an Arduino chip in order to get the readings of the vehicle speed from the speedometer.

Figure 5.11 Loughborough University's Instrumented Vehicle

In order to collect real world data, fifteen real-world trips between Junctions 19 and 21 (northbound and southbound) of the M1 motorway were conducted between April 2018 and December 2018 11:00 to 12:00 am with the assistance of two different drivers who were instructed to drive normally in order to represent an average motorway driver. For the purpose of this thesis, three trips were conducted per weekday (fifteen trips in total) in order to obtain data to calibrate and validate each baseline traffic microsimulation model. The data gathered from the trips were cleansed and fused together using Matlab (Formosa, Quddus and Ison, 2019) and were divided equally into a calibration and validation dataset. The architecture of the data flow between the sensors within the vehicle is presented in Figure 5.12.

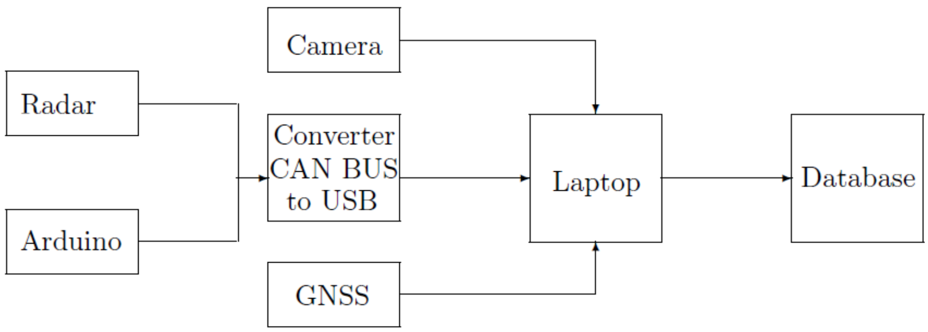


Figure 5.12 Flowchart of the instrumented vehicle data collection process (source: (Formosa, Quddus and Ison, 2019))

It must be emphasized that only radar geographical positioning data are used in this thesis. The sampling frequency of the radar sensor is 15 Hz and the scanning range is 200 meters. The metadata of the raw data that is collected is presented in Table 5.7 and a graphical representation of the collected data is presented in Figure 5.13. The “longitude” and “latitude” variables are collected using the GNSS sensor with a frequency of 1 Hz.

Table 5.7 Metadata of the raw primary radar and GNSS data

Variable name	Description
ID	Number of observation of the dataset
Freq	The frequency counter of the radar
Hour	Current time (hour)
Min	Current time (Minute)
Sec	Current time (Second)
Milli	Current time (millisecond)
ID#	Every time an object was identified by the radar it is given a number and the object is being tracked at every step of the radar frequency. The ID number is stored for the specific object
Obj_LongDispl	The longitudinal displacement between the radar and the object
Obj_LatDispl	The lateral displacement between the radar and the object
Obj_VrelLong	The relative velocity between the ego-vehicle and the detected object
Obj_AccelLong	The longitudinal acceleration of the detected object
Obj_LatSpeed	The lateral velocity of the detected object
Obj_Width	The width of the detected object
Obj_Length	The length of the detected object
Longitude	The longitude of the current geographical position

Latitude	The latitude of the current geographical position

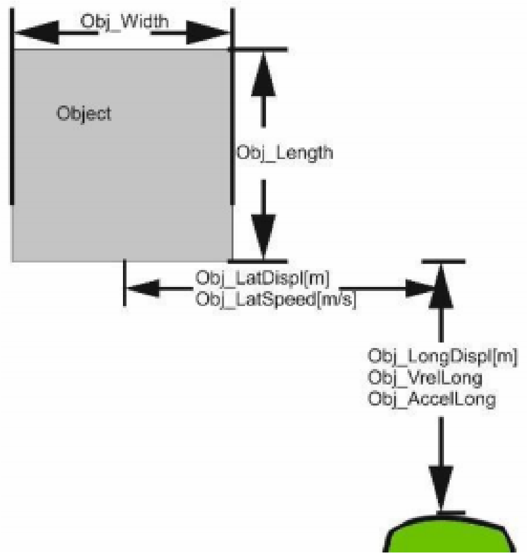


Figure 5.13 Illustration of the data measures by the radar sensor (Schnieder, 2017)

As mentioned in section 4.3.1.2 the raw data collected are processed in order to calculate the Time to Collision (TTC) to the preceding vehicle in the same lane, which is used in the second stage calibration and validation process of the baseline microsimulation models. In order to calculate the TTC value to the preceding vehicle the following process was followed:

- Initially, the raw data were filtered according to the lateral displacement in order to derive vehicles who were in the same lane as the ego-vehicle. The threshold value used for that purpose was 1.75 meters (half the width of the lane).
- Afterwards, the closest object to the ego-vehicle was identified using the longitudinal displacement radar value and the TTC value was calculated for the specific vehicle using the corresponding relative velocity value.

The above process was performed in the statistical software STATA using the following pseudocode which operated for every observation of the dataset.

The final product was a series of TTC values to the preceding vehicle. It must be emphasized that values of TTC greater than 100 seconds were filtered from the dataset as uninformative. The distributions calculated for each weekday are presented in Figure 5.14.

The distributions presented in Figure 5.14 are compared with TTC distributions calculated from the corresponding baseline traffic microsimulation model. That means that the Monday real-world TTC distribution is compared with a TTC distributions calculated through vehicles in the microsimulation software in the Monday model. VISSIM does not provide the users with a TTC distribution by default. Hence, a code is written in this thesis using the External Driver Model API of VISSIM where the vehicle could use the default driver model of VISSIM but it would record the TTC values to the preceding vehicle in a text file. This was done using the following code:

The simulated TTC distributions derived as a result of the code above are compared with the corresponding real-world TTC distribution of Figure 5.14. This comparison was done by employing the non-Parametric Mann-Whitney test which was described in section 4.3.1.2.

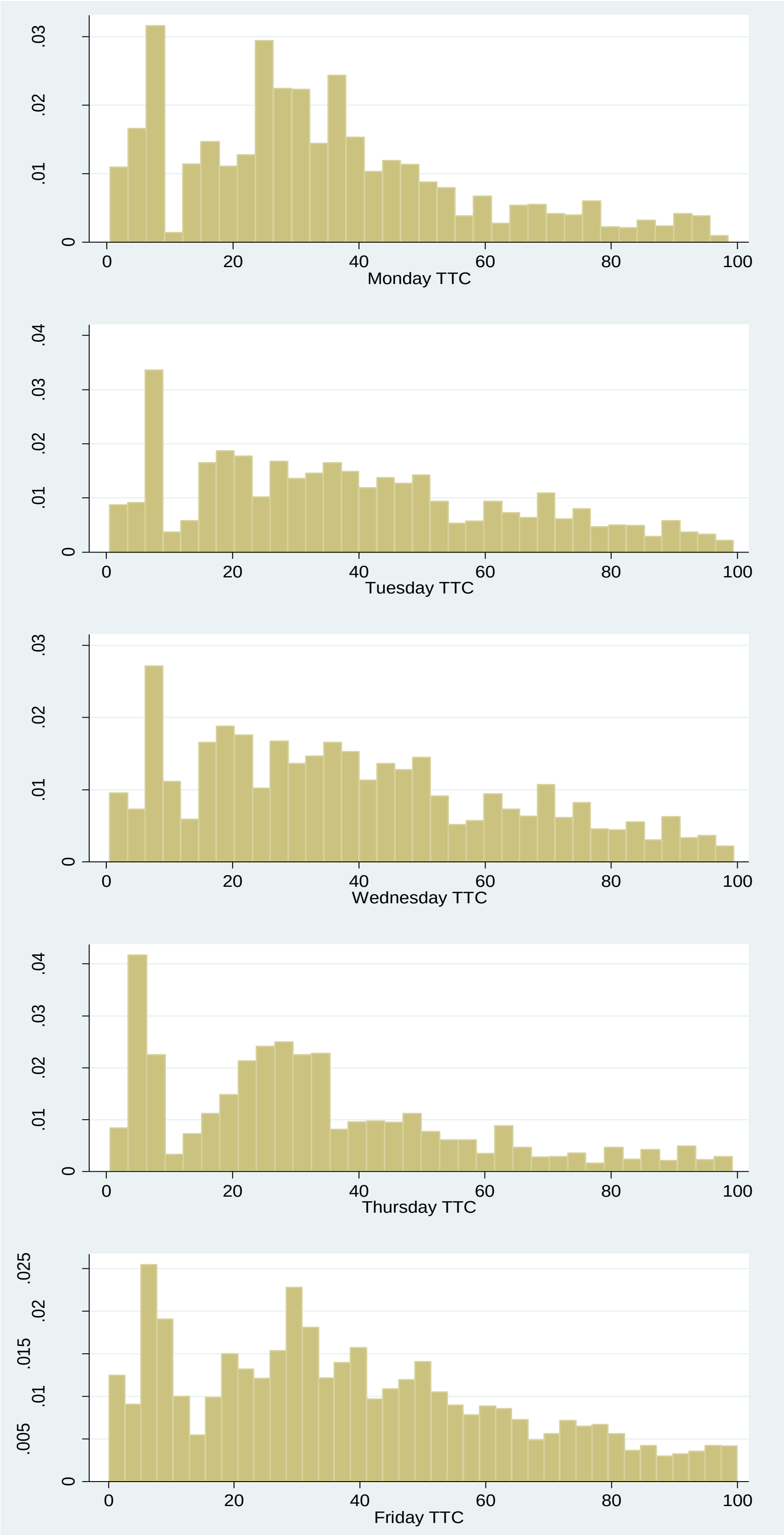


Figure 5.14 Real-world TTC distributions from instrumented vehicle data

The initial indications of the Mann-Whitney tests indicated that there were significant differences between the two compared distributions hence, a calibration of the safety parameters is recommended. The calibration process followed in this thesis was an optimisation problem in order to maximise the U-statistic of the Mann-Whitney test, a fact that could provide stronger evidence for the similarity of the compared distributions.

For this purpose, a sensitivity analysis is conducted to identify the effect of the Wiedemann 99 car following and lane changing model (see section 4.3.1.1) parameters to the TTC distribution produced by the simulation vehicles. The initial list of parameters (see Table 4.2 and Table 4.3) were filtered according to previous studies investigating the effect of VISSIM car-following parameters on simulated safety (Habtemichael and Picado-Santos, 2013). In this thesis the following parameters were found to have a significant effect on the TTC distribution produced by simulated vehicles:

- CC1 – standstill distance (car following)
- CC2 – Following variation (car following)
- CC3 – Threshold for entering following – controls the start of the deceleration process (car following)
- CC5 – Controls the speed variation between lead and following vehicle
- Safety distance reduction factor – reduces the safety distance during lane changing

After manually testing a number of different combinations in order to maximise the Mann-Whitney test value across all weekdays, the parameter CC3 is set to -5 seconds from the default value of -8 seconds. With this change of parameters, the TTC distributions produced by the simulated vehicles are not significantly different from the instrumented vehicle TTC distributions. The Mann-Whitney values of the tests for Monday, Tuesday, Wednesday, Thursday and Friday models were 0.875, 0.716, 0.611, 0.127 and 0.917 accordingly. These values indicate that there was strong evidence to not reject the null hypothesis of the test that the two compared samples originated from the same distribution. The results were validated once again using the validation dataset. The average TTC distribution calculated through VISSIM after the change of CC3 is presented in Figure 5.15.

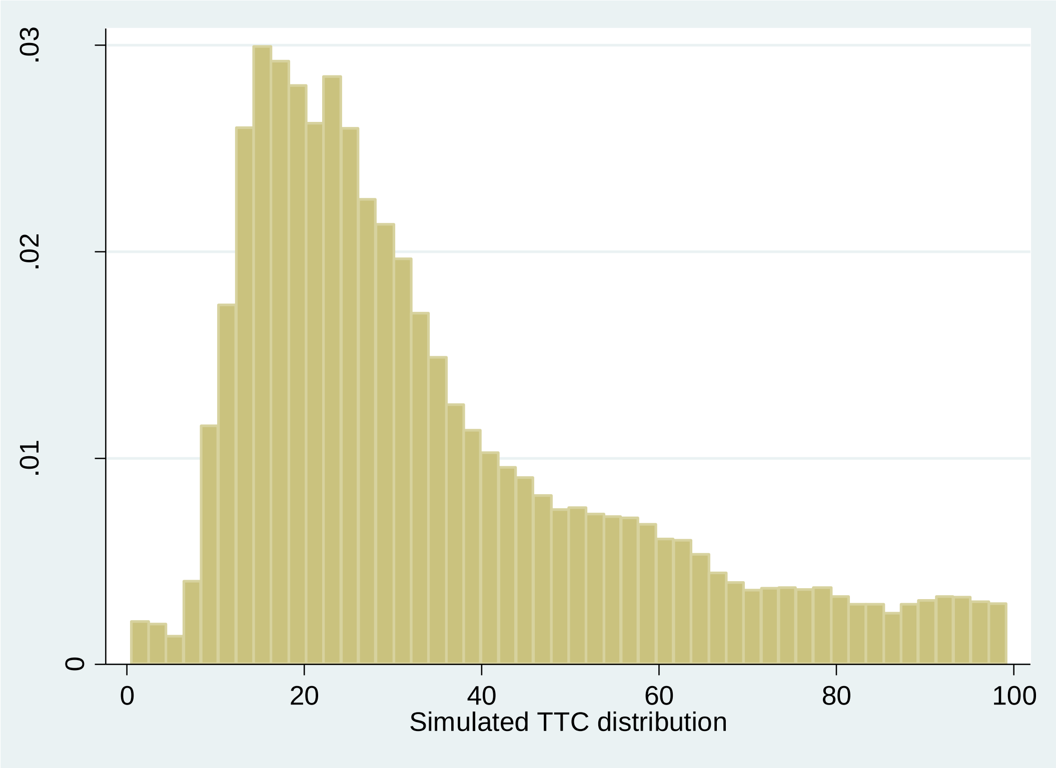


Figure 5.15 Simulated TTC distribution

5.3.1 Limitations of the instrumented vehicle data

This dataset provided by the Loughborough University instrumented vehicle and its sensors provided a solid base for the second stage calibration and validation process of the baseline microsimulation models. The calibration and validation process based on the TTC distribution is novel and never before found in existing literature.

However, a limitation lies on its sample size. Ideally, data from more real-world trips and from a larger number of drivers should be used in order for the sample to be representative. Finally, the algorithm that detects the preceding vehicle from the radar data could be improved. The author is looking into improving this in the future.

5.4 Conflict Data

The final dataset employed for this thesis is a dataset containing simulated traffic conflicts with corresponding traffic characteristics measurements. The purpose of this dataset is to be used as a dataset for the statistical modelling of the traffic conflicts.

The raw data for this dataset is provided by the traffic microsimulation software. The user of VISSIM has the option to assign data collection points in the simulated network which mimic the functionality of inductive loop detectors (see Figure 5.16). In order to form this dataset, several such data collection points are placed in the southbound mainline corridor of the simulated network. In order to mimic the accuracy of inductive loop detector measurements, the data collection points are placed every 400 meters of the corridor resulting in the formulation of 54 segments (See sketch of Figure 5.17).

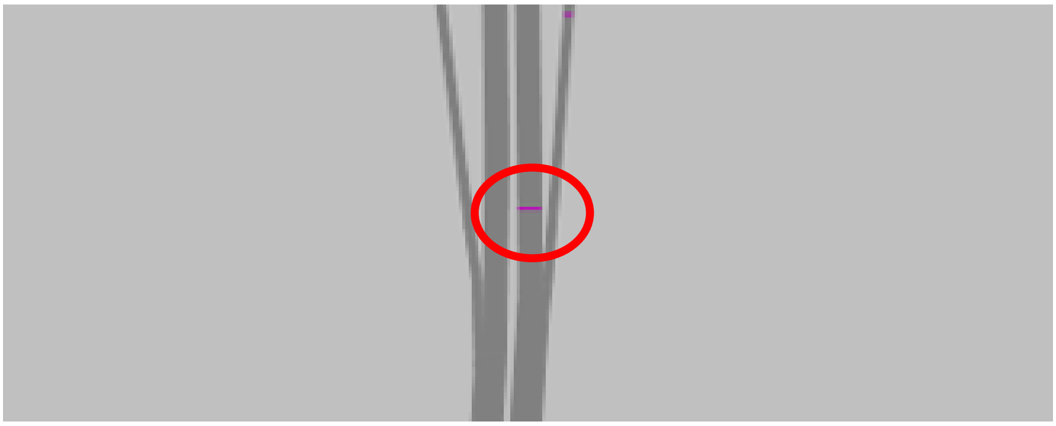


Figure 5.16 A data collection point in VISSIM

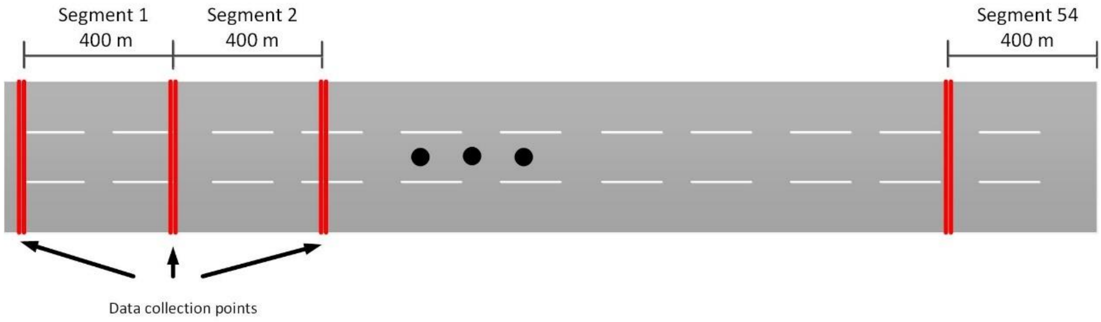


Figure 5.17 Segment identification in VISSIM (not in scale)

The data collection points can record a number of variables for every vehicle that stepped over them in the simulated environment. The list of variables is presented below.

Table 5.8 Data collection point measurements in VISSIM

Variable	Description
Measurement	Unique identification number of the data collection point
T(Entry)	Time that the front bumper of the recorded vehicle was over the data collection point
T(Exit)	Time that the rear bumper of the recorded vehicle was over the data collection point
VehNo	Unique identification number of the recorded vehicle
VehicleType	Type of the recorded vehicle
Velocity (km/h)	Instantaneous speed of the recorded vehicle
Acceleration/Deceleration(m/s^2)	Instantaneous acceleration of the recorded vehicle
Occupancy	Percentage of time that the vehicle occupied the data collection point
Queue time	Time in seconds that the recorded vehicle remained in a queue in the simulated environment over the data collection point
Vehicle length	Length of the recorded vehicle

The raw data gathered from the data collection points are post processed in order to calculate several variables which are used as explanatory variables in the statistical modelling of traffic conflicts. Average measurements (for all 15 simulation runs) for traffic flow per lane and average speed per lane, standard deviation of speeds within lanes and between lanes are calculated directly through the raw measurements of the data collection points and aggregated per market penetration rate level per segment. That practically means that there is one observation per segment per CAV market penetration scenario tested. In order to produce a more detailed dataset for statistical analysis, the market penetration scenarios ran to form this dataset are defined by a constant 10% market penetration rate interval (10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and 100%).

Additionally, as mentioned previously, SSAM is able to provide the user with location of the traffic conflict. Hence, the geographic location of the segments was manually matched with the corresponding number of traffic conflicts identified by SSAM and the two were fused together. Furthermore, the number of spinal points that were necessary in order to simulate the curvature of each segment was manually recorded in a dataset and was fused together with the conflict/data collection measurement dataset. Furthermore, the segments are categorised in merging or diverging areas and straight (non-merging) segments. The result of this data integration process resulted in a dataset which contained the following variables (see Table 5.9). Table 5.10 presents the descriptive statistics of the explanatory variables of Table 5.9.

Table 5.9 Definition of variables of the traffic conflict dataset

Variable	Description
segid	Segment identification number (1-54)
Avgspeedsegment	Average speed observed among all lanes in the segment
Speed1	Average speed in the outermost lane of the segment
Speed2	Average speed in the middle lane of the segment
Speed3	Average speed in the innermost lane of the segment
Globalavgspeed	Average speed in the whole simulation network (constant)
Stdspeed1	Standard deviation of speeds within vehicles in the outermost lane of the segment
Stdspeed2	Standard deviation of speeds within vehicles in the middle lane of the segment
Stdspeed3	Standard deviation of speeds within vehicles in the innermost lane of the segment
Flow1	Traffic flow in vehicles/hour for the outermost lane of the segment
Flow2	Traffic flow in vehicles/hour for the middle lane of the segment

Flow3	Traffic flow in vehicles/hour for the innermost lane of the segment
Totflow	Total traffic flow in vehicles/hour for all the lanes of the segment
Occupancy	Average occupancy of the data collection point
Stdbetween	Standard deviation of speeds between lanes
Merge	Dummy variable explaining whether a segment was a merging or divering area (1 if merging/diverging, 0 otherwise)
mpr	Market penetration rate of CAVs
Curvature	Number of spinal points of the segment
Conflicts	Number of corresponding traffic conflicts calculated through SSAM

Table 5.10 Descriptive statistics of the variables of the traffic conflict dataset

Variable	**Mean**	**Std.Dev**	**Min**	**Max**
segid			1	54
Avgspeedsegment	99.05	4.40	92.92	108.94
Speed1	100.56	5.01	93.25	110.091
Speed2	98.42	4.33	92.46	108.87
Speed3	97.56	4.16	92.78	108.52
Globalavgspeed	98.85	4.35	94.06	107.10
Stdspeed1	8.44	1.48	3.68	11.62
Stdspeed2	7.66	2.27	3.62	11.49
Stdspeed3	7.65	2.12	3.41	11.01
Flow1	389.79	114.59	207.87	654
Flow2	668.78	91.54	396.93	855.375
Flow3	563.68	117.86	137.68	817.81
Totflow	1622.26	192.71	1068.375	1868.467
Occupancy	0.049	0.0001	0.049	0.050
Stdbetween	1.6290	0.8352	0.2802	4.170014
Merge	0.074	0.26	0	1
Curvature	6.74	3.25	2	15
Conflicts	2.40	3.32	0	33

5.4.1 Limitations of the conflict dataset

The traffic flow characteristics included in the traffic conflict dataset are provided by VISSIM. It is a highly disaggregated dataset and the model has been calibrated and validated in order to produce realistic baseline outputs. The number of traffic conflicts in the dataset are provided by SSAM and matched with the corresponding motorway segment. The integrated dataset can provide a solid base for the statistical analysis in this thesis. However, it can never replace a real-world dataset containing real-world measurements and the corresponding traffic conflicts. On the other hand, such a dataset would be out of the scope of this simulation-focused thesis. Hence, the statistical results should be interpreted carefully as they model the occurrence of traffic conflicts based on the traffic microsimulation conditions.

Finally, the number of the traffic conflicts itself is not calibrated as real-world traffic conflict data are not available for this study. However, it is assumed that with the second stage calibration and validation the main surrogate measure (TTC) used for the conflict identification is calibrated and hence, indirectly the number of conflicts is calibrated.

5.5 Summary

This chapter presented the datasets used for the purpose of this thesis as well as the simulation study area. The study area contains a section of the M1 motorway in the United Kingdom between Junctions 19 and 21. The study area as well as the reasons behind the choice of this area are explained in detail in the first subsection of this chapter.

Subsequently, the next two sections of this chapter presented in detail the formulation and the meta data of the two datasets which were used for the calibration and the validation of the baseline traffic microsimulation models.

The first dataset was used for the first stage of the calibration process which ensured the accurate representation of traffic characteristics within the simulation environment. It comprised of secondary inductive loop detector data which were processed in order to be used as input for the microsimulation models and were divided into a calibration and validation dataset. The results of this first stage indicated that no further adjustments were needed in the default Wiedemann 99 driver model parameters of VISSIM.

The instrumented vehicle dataset was used for the second stage calibration and validation of the microsimulation. It comprised of processed radar and GNSS data collected through fifteen real-world trips, which assisted with the calculation of several real-world Time-to-Collision (TTC) distributions. These distributions were compared with simulated TTC distributions and as a result, the parameter CC3 of the Wiedemann 99 model was calibrated in order for the two distributions to not be significantly different.

Finally, the formulation of the traffic conflict dataset was described in detail. The simulated conflicts calculated through SSAM were matched with the corresponding simulated traffic data collected using the data collection points of VISSIM. The resulting dataset contained the conflict count and a number of corresponding explanatory variables which will are used for the statistical analysis of this thesis.

6 Results and Discussion

6.1 Introduction

This chapter of the thesis will present the results derived by employing the methods described in Chapter 4, using the datasets presented in Chapter 5. Undoubtedly, the main methods described above are the traffic microsimulation and the statistical modelling, hence, firstly, the traffic microsimulation results are presented and discussed with regards to their methodological implications and fit within the existing literature and the statistical modelling results follow.

In more detail, this chapter is organised as follows;

- ❖ Simulation framework results
    - Weekday scenario results (Scenarios 1 to 25)
    - Route-based decision-making algorithm scenario results (Scenarios 26 to 29)
    - Sensor error scenario results (Scenarios 30 to 45)
    - Platoon size scenario results (Scenarios 46 to 61)
- ❖ Statistical modelling results

The simulation framework results will present the number of conflicts calculated for each formulated scenario by SSAM along with corresponding explanatory graphs and a number of descriptive statistics for the surrogate safety measure Time to Collision identified for the conflicts of each scenario, when it is deemed necessary. For each scenario, 15 simulation runs were performed with different random seeds. Each simulation run lasted 3600 seconds with extra 900 as a warm-up period to allow the simulation network to be fully occupied which was excluded from the analysis. It must be noted that as the CAV market penetration rate increased in the various scenarios the computation time increased significantly. For instance, the 0% market penetration rate scenario lasted in average 30 minutes while a simulation run with 100% CAV market penetration rate lasted approximately 45 minutes. In order to facilitate the understanding of the results, in most of the scenarios and where this needed, the calculated conflicts will be presented in heatmaps describing the spatial distribution of traffic conflicts on the motorway network. The simulation results are discussed on the basis of their fit with existing literature, the underlying assumptions and the practical implications.

The statistical modelling results will present the coefficient estimates of the examined independent explanatory variables. Also, the correlation between the independent variables is discussed. Finally, the practical implications of the statistical modelling results are discussed.

6.2 Simulation Framework Results

6.2.1 Weekday scenario results (Scenarios 1 to 25)

The absolute change in the number of traffic conflicts per market penetration rate and weekday is initially presented in Figure 6.1. In order to normalise these results for comparison purposes, the absolute number of conflicts is converted into percent change in the number of conflicts in Table 6.1.

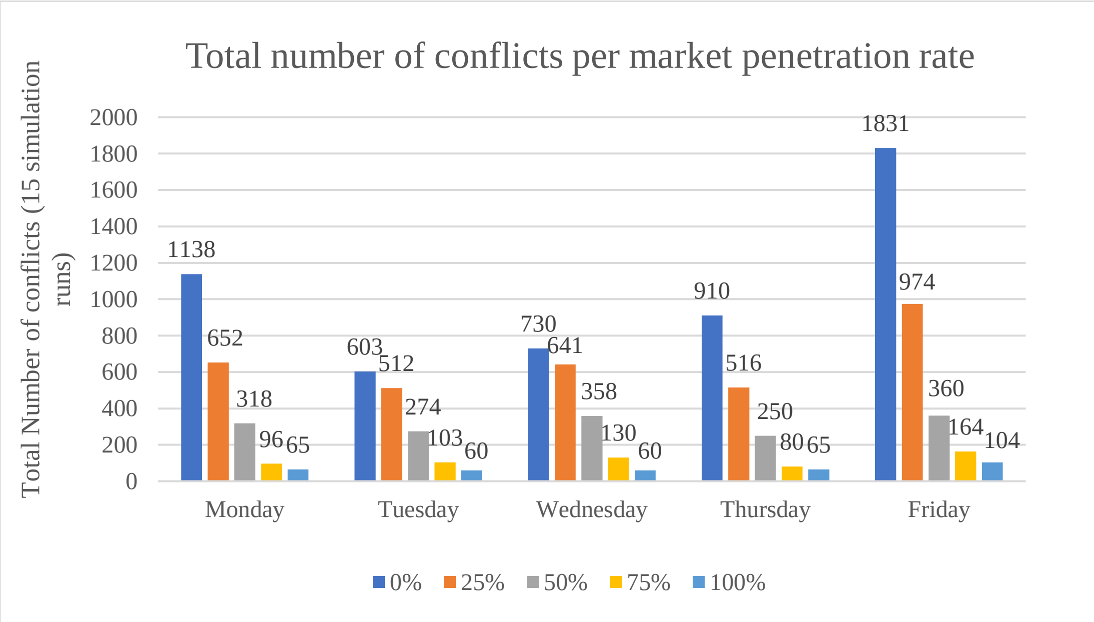


Figure 6.1 Number of traffic conflicts per market penetration scenario (Scenarios 1-25)

Table 6.1 Percent change in the number of conflicts (Scenarios 1-25)

	Total Conflict Reduction %					**% conflicts involving CAVs**
	Monday	Tuesday	Wednesday	Thursday	Friday	
0%	0.00%	0.00%	0.00%	0.00%	0.00%	N/A
25%	42.71%	15.09%	12.19%	43.30%	46.81%	4.85%
50%	72.06%	54.56%	50.96%	72.53%	80.34%	14%
75%	91.56%	82.92%	82.19%	91.21%	91.04%	40%
100%	94.29%	90.05%	91.78%	92.86%	94.32%	100%

The reduction of conflicts at the 100% market penetration rate varies between 90-94%. At first glance, this reduction in simulated conflicts seems to be very close with the anticipated safety benefit of CAVs according to the literature (Daniel J. Fagnant and Kockelman, 2015). However, the results should not be considered identical. A reduction of 90-94% in traffic conflicts which was calculated in this thesis does not necessarily imply a 94% reduction in accidents which was predicted in the literature. A functional relationship between conflicts and crashes can be found in Gettman *et al.*, (2008), although, the authors of this paper mention that the functional relationship developed is not transferable and hence cannot be used in this thesis to calculate the results on accidents.

Figure 2.2 in the literature review chapter originally summed results found in similar studies namely Kockelman *et al.*, (2016) and Jeong, Oh and Lee, (2017). Figure 6.2 adds the results of this section in Figure 2.2. Initially, the results presented in this thesis seem to be very close with the results of Jeong Oh and Lee (2017), especially in the Tuesday and Wednesday scenarios. Additionally, even though the same weekday scenarios seem to provide similar results to the “high traffic flow” scenarios of Kockelman et al (2016), the traffic flow values used in these scenarios were significantly different as Tuesday and Wednesday scenarios traffic flow values (1500 vehicles per hour approximately) were 50% less than the traffic flow values used in Kockelman et al. (3000 vehicles per hour). Most importantly, a comparison of the results of these studies might be invalid due to the fact that the underlying CAV models and assumptions varied significantly between the compared studies. For example, Kockelman et al (2016) used Wiedemann 99 car following model without any variance in the behaviour parameters in order to simulate a CAV driving behaviour whereas a completely different CAV driver model is developed in this thesis.

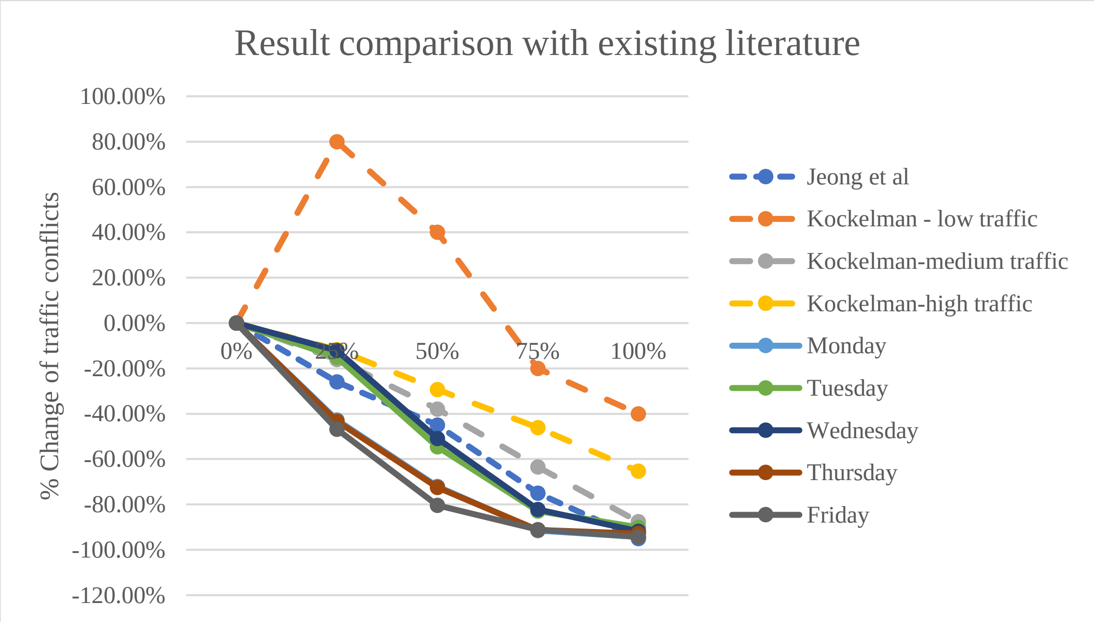


Figure 6.2 Comparison of results with literature findings

Following, a major reduction of conflicts is clear from Table 6.1 even at small market penetration rates, which proves the effectiveness of the developed algorithm to reduce the number of conflicts significantly. However, even though one would expect the CAV behaviour algorithm to not have any flaws, still a small number of conflicts is observed at the 100% market penetration rate scenarios. These few conflicts could happen due to imperfections in the simulation software or as a consequence of a slow speed lane-changing manoeuvre in the motorway merging areas (if a required time-gap for lane change was not identified, vehicles were forced to stop according to the rules of the software).

It is noteworthy that the safety performance of the algorithm at the 25% market penetration rate is improving as traffic flow increases. For example, on Fridays, that the traffic flow is the highest, a greater reduction of conflicts is observed at the 25% market penetration rate than on lower traffic weekdays (e.g. Wednesday).

Furthermore, a possible explanation for the relatively small improvement from 75% to 100% market penetration rates could be the fact that even from 75%, CAVs tended to form long platoons (8+ vehicles), isolating human driven vehicles in their own lanes and making the interactions between human driven vehicles minimal. Finally, it is observed that percentage of conflicts involving CAVs is significantly lower than the corresponding market penetration rate.

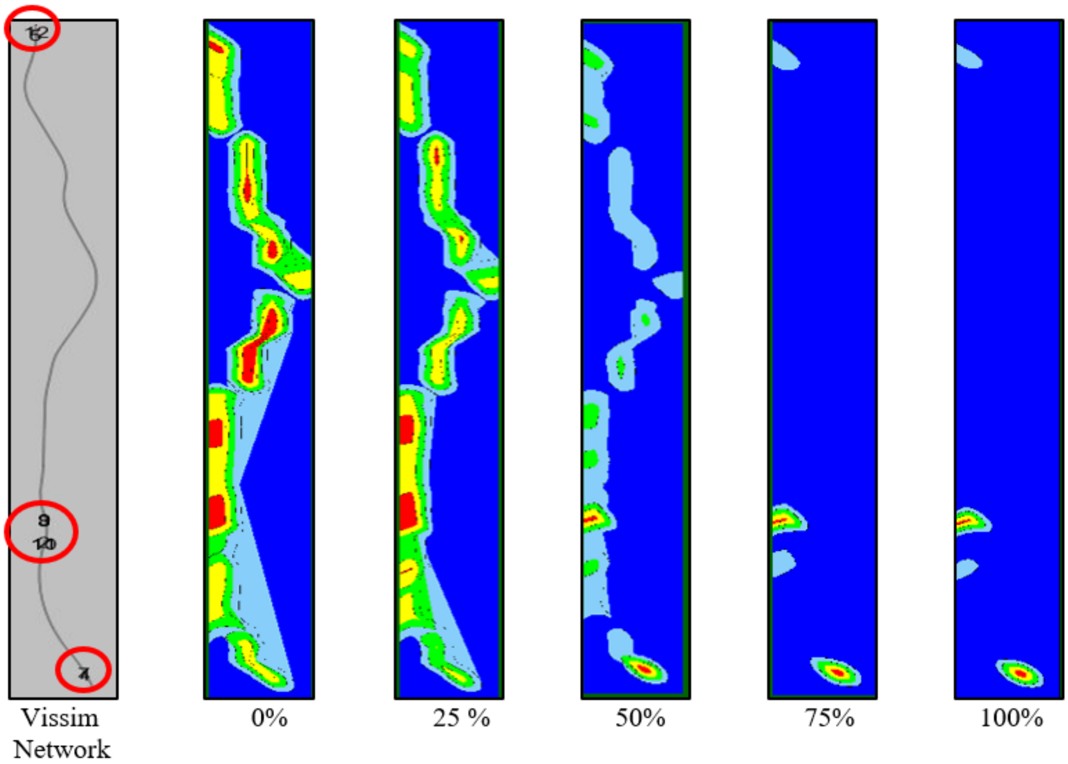


Figure 6.3 Heatmap of the concentration of traffic conflicts across the motorway network among all weekdays

Figure 6.3 presents the heatmaps showing the concentration of conflicts across the motorway segment per market penetration scenario. Unfortunately, the scale of the heatmaps cannot be provided as it varied across different heatmaps. However, it can be interpreted in relation to the number of conflicts. It is obvious that the CAV control algorithm eliminates conflicts in the non-merging/diverging areas in high market penetration rate scenarios effectively. Inevitably, a high number of conflicts is observed at the merging and diverging areas (Junctions 21, 20 and 19 of the motorway, marked with a red circle in the left-most graph of Figure 6.3) due to the high variance of speeds and number of lane changes that take place on those segments. This finding seems to agree with relevant literature characterising the merging and diverging areas of the motorway as high risk segments (Ahammed, Hassan and Sayed, 2008).

Table 6.2 can shed more light on this issue; it provides the percentage of each conflict type per market penetration rate. The percentage of lane changing conflicts is coming close to the percentage of rear end conflicts as market penetration rate increases (although the absolute number of conflicts is reduced significantly). All the conflicts in the high market penetration rate scenarios (i.e. 75% and 100%) are concentrated in or near the merging and diverging areas where lane changing behaviours are enforced. (see Figure 6.3) The lane changing conflicts happening in this area are a product of the actual lane changing manoeuvres and the rear-end conflicts are potentially a consequence of the situation arising after the lane change manoeuvre takes place.

Table 6.2 Percentage of type of conflicts per market penetration scenario

Market Penetration Rate	Rear end	Lane change
0%	9.18%	90.82%
25%	22.55%	77.45%
50%	23.26%	76.74%
75%	32.56%	67.44%
100%	43.68%	56.32%

The SSAM output indicated that in all market penetration rates, the minimum TTC value observed was 0 seconds, which implied a vehicle collision (see Table 6.3). Some of the previous papers filter out these zero values claiming that they are caused by simulation errors (Gettman *et al.*, 2008). However, others keep these virtual crashes in the analysis (Shahdah, Saccomanno and Persaud, 2015). After close observation of the behaviour of the vehicles in VISSIM some of these conflicts might have been caused due to simulation error; in the mainline vehicle input points, vehicles started a lane change at the same moment when another vehicle just entered the motorway resulting in a virtual crash. This problem was resolved partially by not allowing a lane change in the first 50 meters of the simulation network input points.

However, this problem persisted. To clarify, it is observed that there is an abrupt change in the mean of the TTC values from market penetration rates lower than 75% to the market penetration rate of 100%. This provides strong evidence for the argument of the previous paragraph; the human driver model of Vissim is the main source of conflicts with 0 TTC value.

Table 6.3 Descriptive statistics of the TTC value provided by SSAM per scenario

	TTC			
Scenario	**Min**	**Max**	**Mean**	**Variance**
0% Monday	0.00	1.50	0.13	0.11
25% Monday	0.00	1.50	0.14	0.11
50% Monday	0.00	1.50	0.12	0.11
75% Monday	0.00	1.50	0.13	0.14
100% Monday	0.00	1.50	0.83	0.33
0% Tuesday	0.00	1.40	0.12	0.10
25% Tuesday	0.00	1.50	0.14	0.12
50% Tuesday	0.00	1.50	0.11	0.09
75% Tuesday	0.00	1.50	0.14	0.13
100% Tuesday	0.00	1.50	0.56	0.40
0% Wednesday	0.00	1.50	0.10	0.08
25% Wednesday	0.00	1.50	0.12	0.10
50% Wednesday	0.00	1.50	0.11	0.10
75% Wednesday	0.00	1.50	0.11	0.10
100% Wednesday	0.00	1.50	0.54	0.21
0% Thursday	0.00	1.50	0.14	0.12
25% Thursday	0.00	1.50	0.12	0.11
50% Thursday	0.00	1.50	0.13	0.11
75% Thursday	0.00	1.50	0.14	0.14
100% Thursday	0.00	1.50	0.99	0.37
0% Friday	0.00	1.50	0.15	0.12
25% Friday	0.00	1.50	0.11	0.09
50% Friday	0.00	1.50	0.17	0.15
75% Friday	0.00	1.50	0.18	0.18
100% Friday	0.00	1.50	0.64	0.43

Finally, although the focus of this thesis is to evaluate the safety impact of CAVs, in order to obtain more complete understanding of the impacts of CAVs, the travel time impact of the proposed algorithm was calculated as well and is presented in Table 6.4.

CAVs seem to increase the average travel time during all weekdays due to the fact that long vehicle platoons with a slow leader (the speed of the leader was selected from the desired speed distribution and hence it is stochastic) decreased the average speed of the motorway. This result however is sensitive to the desired speed distribution of vehicles in VISSIM. Overall, it is observed that, at the 100% market penetration scenario, CAVs managed to make the travel time almost equal across all weekdays. This means that CAVs will be able to provide reliable travel times independent of traffic conditions, a result that seems to agree with previous studies (ATKINS, 2016b).

Table 6.4 Average travel time results for simulated vehicles for each CAV market penetration scenario

	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
	Travel Time (sec)	Travel Time (sec)	Travel Time (sec)	Travel Time (sec)	Travel Time (sec)
0%	727.28	751.0	748.3	796.9	822.2
25%	820.88	805.1	804.0	830.0	849.76
50%	843.01	835.1	835.3	848.8	858.30
75%	861.89	859.3	859.4	864.2	866.00
100%	874.03	874.2	874.5	875.1	874.00

6.2.2 Route-based decision algorithm results (Scenarios 26 to 29)

This section presents the traffic conflict results for the scenarios were the route-based decision-making algorithm (RBDMA) for CAVs is tested. It must be emphasized that the models ran for the comparison with the baseline (no RBDA) scenario was the Wednesday model which represented a typical weekday.

Initially, the reduction of the total number of conflicts per CAV market penetration rate is presented in Figure 6.4.

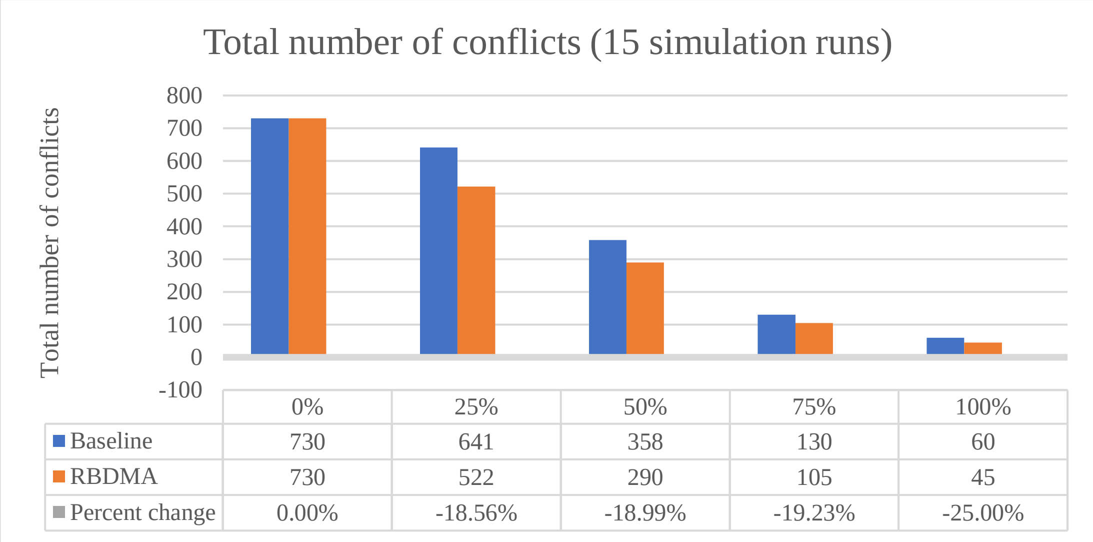


Figure 6.4 Total number of conflicts reductions due to the route-based decision-making algorithm

It is observed that the RBDMA has a positive safety effect. It reduces the number of traffic conflicts by 18.56%, 18.99%, 19.23%, 25.00% in the 25%, 50%, 75% and 100% market penetration rates respectively. It has to be noted that the percent reduction of conflicts increases as the CAV market penetration rate increases. This is undoubtedly because as the market penetration rate of CAVs and the relative number of CAVs in the network becomes larger, they form more vehicle platoons which are driving in the correct lane according to their destination and consequently the number of unnecessary lane changes that could potentially be proven to be traffic conflicts decrease.

Table 6.5 Time to Collision descriptive statistics for the route-based decision algorithm scenarios

	TTC			
Scenario	**Min**	**Max**	**Mean**	**Variance**
RBDMA 25%	0	1.5	0.15	0.14
RBDMA 50%	0	1.5	0.22	0.21
RBDMA 75%	0	1.5	0.5	0.31
RBDMA 100%	0	1.5	0.75	0.35
0% Baseline	0	1.5	0.1	0.08
25% Baseline	0	1.5	0.12	0.1
50% Baseline	0	1.5	0.11	0.1
75% Baseline	0	1.5	0.11	0.1
100% Baseline	0	1.5	0.54	0.21

Table 6.5 presents the descriptive statistics of the TTC values for the conflicts calculated for the RBDMA scenarios. A significant increase in the mean value of the TTC is observed which becomes larger as the market penetration rate of CAVs increases. This change can be attributed to the fact that due to the assignment of the platoons in lanes according to the corresponding destinations, significantly less CAV lane changes are taking place. This consequently means that even from the low market penetration rates, the interactions between CAVs and human-driven vehicles become less and cases where a low TTC value would be observed because of a "forced" lane change (in order to reach the next link of a vehicle's destination) are reduced.

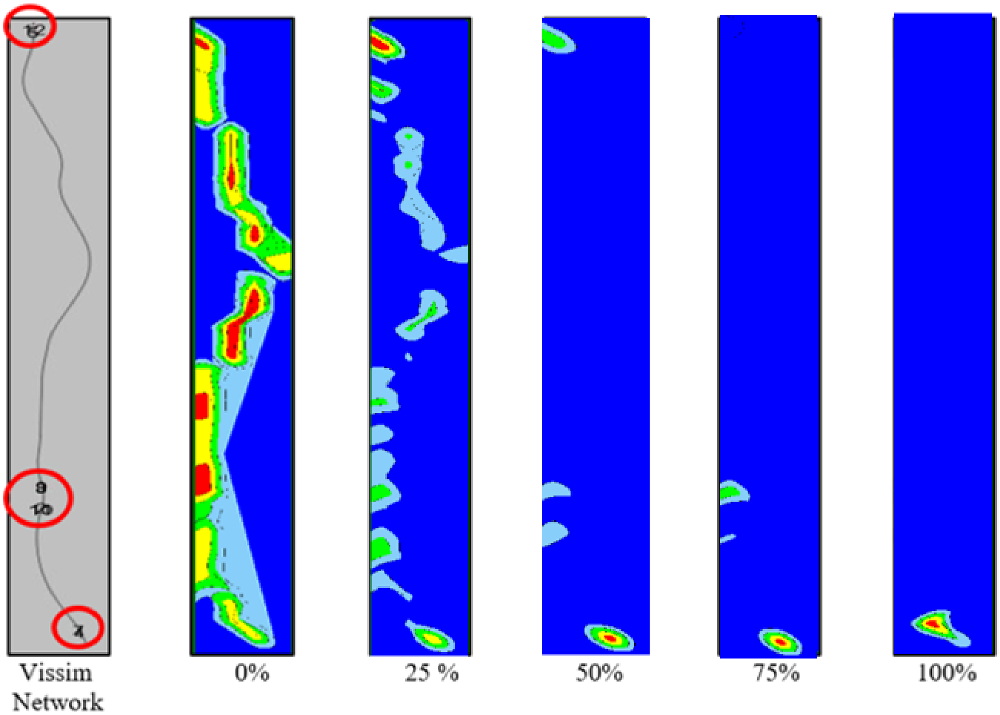


Figure 6.5 Heatmap of traffic conflicts in the RBDMA scenarios

Figure 6.5 presents the heatmap showing the concentration of conflicts across the simulated motorway network. If one compares Figure 6.5 with Figure 6.3, it can be observed that the RBDMA has improved safety in the motorway significantly. However, the same issue observed in scenarios 1-25 persists but in smaller magnitude;

The merging and diverging areas of Juctions 19, 20 and 21 remain problematic as they appear to concentrate a large number of conflicts which is in line with literature. However, compared to scenarios 1-25 RBDMA the number of conflicts in these areas seems to be reduced. For instance, the RBDMA at the 75% market penetration rate seems to eliminate the traffic conflicts in junction 21 (North junction) and at 100% in junction 20. The problem still persists though in Junction 19.

Trying to compare the results presented in this section with similar results from literature is a challenging task. The objective to develop the RBDMA was among the research gaps identified in the literature; To the author's knowledge there are no studies employing traffic micro-simulation and a route-based decision-making algorithm. There are however studies attempting to fit a dynamic origin to destination routing of CAVs in motorway networks but not in traffic microsimulation environments (Roncoli, Papamichail and Papageorgiou, 2015; Davis, 2017). The results of these studies were limited and only assessed the performance of the developed algorithm with regards to traffic performance of the network and not safety. The algorithms of the aforementioned studies were more complex than the RBDMA developed in this thesis, however its simple nature consisted the collection of results a feasible task.

6.2.3 Sensor error scenario results (Scenarios 30 to 45)

This section presents the traffic conflicts results calculated by the traffic microsimulation scenarios where the sensor error rates were included. The sensor error rates chosen for this thesis were defined as pairs of standard deviation in the measurements of speed and distance. As described in section 4.3.1.3 these pairs were derived based on the error rate values of existing equipment found in CAVs such as a typical radar. The pairs tested were (0.05, 0.05), (0.10, 0.06), (0.15, 0.07) and (0.20, 0.08) for (distance measurement standard deviation (meters), speed measurement standard deviation (meters/second)).

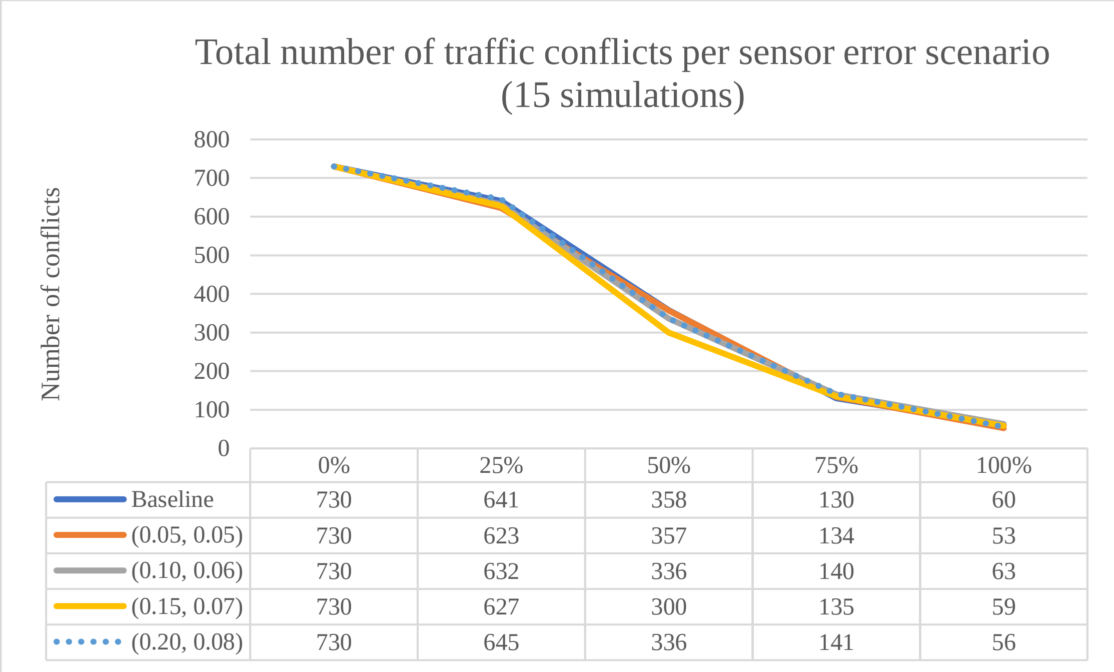
Initially, the total number of conflicts produced from all 15 simulation runs per sensor error scenario are presented in Figure 6.6. The safety benefit of CAVs is obvious as market penetration rate increases throughout all sensor error values. However, at first glance, the differences in simulated conflicts under different of sensor error scenarios seemed to not differ significantly from the baseline model. To confirm this observation, four iterations of a statistical test were performed. The non-parametric multiple independent samples Kruskal-Wallis test was applied to test whether the difference in in the number conflicts differed significantly by sensor error rate scenario. The Kruskal-Wallis rank test also known as one-way ANOVA on ranks, is a non-parametric method for testing whether samples originate from the same distribution. It is used for comparing two or more independent samples of equal or different sample sizes and therefore it is deemed appropriate for the comparison of the number of conflicts per sensor error scenario. A significant Kruskal-Wallis test indicates that at least one sample stochastically differs from one other sample, but it cannot identify how or where this stochastic difference occurs. In order to perform this test, the H value (see equation (6.1)) is compared with the critical H value which is calculated from a table or a statistical software.

$$H = (N-1)\frac{\sum_{i=1}^{g} n_i(\overline{r_i} - \overline{r})^2}{\sum_{i=1}^{g}\sum_{j=1}^{n_i}(r_{ij} - \bar{r})^2} \tag{6.1}$$

Where:

- n_i is the number of observations in group i
- r_{ij} the rank (among all observations) of observation j from group i
- N the total number of observations across all groups
- $\overline{r_i}$ the average rank of all observations in group i
- $\bar{r}$ the average of all the $\overline{r_i}$

For the purpose of this thesis this test was performed in the SPSS statistical software. The p-value of the tests calculated were 0.649, 0.505, 0.420, 0.404 for the sensor error pairs of (0.05, 0.05), (0.10, 0.06), (0.15, 0.07) and (0.20, 0.08) accordingly and indicated that the null hypothesis that the samples originate from the same distribution could be retained at the 95% confidence level. The mean and standard deviation values of the samples used in the Kruskal Wallis tests are presented in Table 6.6.



	0%	25%	50%	75%	100%
Baseline	730	641	358	130	60
(0.05, 0.05)	730	623	357	134	53
(0.10, 0.06)	730	632	336	140	63
(0.15, 0.07)	730	627	300	135	59
(0.20, 0.08)	730	645	336	141	56

Figure 6.6 Total number of conflicts per sensor error scenario

Table 6.6 Descriptive statistics of samples used in the Kruskal Wallis sensor error rate tests

Scenario	**Market penetration rate**				
	0% (mean, s.d.)	**25% (mean, s.d.)**	**50% (mean, s.d.)**	**75% (mean, s.d.)**	**100% (mean, s.d.)**
Baseline	(48.67, 2.26)	(42.73, 2.44)	(23.86, 2.14)	(8.66, 2.16)	(4.00, 2.02)
(0.05, 0.05)	(48.67, 2.26)	(41.50, 2.04)	(23.80, 3.58)	(8.90, 2.71)	(3.50. 3.15)
(0.10, 0.06)	(48.67, 2.26)	(42.10, 3.50)	(22.40, 2.44)	(9.30, 2.96)	(4.20, 3.63)
(0.15, 0.07)	(48.67, 2.26)	(41.80, 3.15)	(20.00, 2.03)	(9.00, 2.35)	(3.90, 2.22)
(0.20, 0.08)	(48.67, 2.26)	(43.00, 3.00)	(22.40, 2.94)	(9.40, 3.42)	(3.70, 2.99)

From one point of view, the result above is logical. In these scenarios, the sensor error assumed to follow a Gaussian distribution N= $(0,\sigma^2)$ with zero mean in order not to cause observation bias and a small standard deviation compared to the average measured values. For example, in a formulated platoon that is driving with a speed of 28 m/s (100 km/h) and a time gap of 0.6 seconds (17.8 meters at the speed of 100 km/h) a sensor error of 0.1m for distance measurement and 0.1 m/s for the speed measurement of the leading vehicle is not be sufficient to cause additional traffic conflicts. This distribution of the sensor error is an assumption of the thesis based on existing literature.

Table 6.7 provides the descriptive statistics for the conflicts calculated in the sensor error rate scenarios. No clear downward or upward pattern can be observed using this table; hence it is assumed that the nature of conflicts remains the same throughout these scenarios.

Table 6.7 Time to Collision descriptive statistics for sensor error rate scenarios

Scenario	TTC descriptive statistics			
	Min	Max	Mean	Variance
(0.05, 0.05) 25%	0	1.5	0.12	0.11
(0.05, 0.05) 50%	0	1.5	0.12	0.11
(0.05, 0.05) 75%	0	1.5	0.11	0.10
(0.05, 0.05) 100%	0	1.5	0.26	0.23
(0.10, 0.06) 25%	0	1.5	0.11	0.10
(0.10, 0.06) 50%	0	1.5	0.10	0.09
(0.10, 0.06) 75%	0	1.5	0.12	0.10
(0.10, 0.06) 100%	0	1.5	0.23	0.20
(0.15, 0.07) 25%	0	1.5	0.13	0.10
(0.15, 0.07) 50%	0	1.5	0.11	0.09
(0.15, 0.07) 75%	0	1.5	0.10	0.08
(0.15, 0.07) 100%	0	1.5	0.25	0.22
(0.20, 0.08) 25%	0	1.5	0.12	0.10
(0.20, 0.08) 50%	0	1.5	0.11	0.09
(0.20, 0.08) 75%	0	1.5	0.10	0.09
(0.20, 0.08) 100%	0	1.5	0.23	0.20
Baseline 0%	0	1.5	0.10	0.08
Baseline 25%	0	1.5	0.12	0.10
Baseline 50%	0	1.5	0.11	0.10
Baseline 75%	0	1.5	0.11	0.10
Baseline 100%	0	1.5	0.24	0.21

The main conclusion from the sensor error rate scenario results regards the readiness level of existing equipment found in CAVs. Under the assumptions of this thesis, the number of traffic conflicts remained the same within the same market penetration rate as the standard deviation of the sensor error rate increased. This potentially proves that existing vehicle equipment (i.e. long range radars) used in the automotive industry are reliable enough so as to not cause any further traffic conflicts due to their inaccuracies.

However, as mentioned above, the reliability of the results presented above must be considered together with the accompanying assumptions. The assumptions made for the sensor errors are logical and they were derived based on evidence found in the literature (Zhou *et al.*, 2017). The sensor error was assumed to be normally distributed with zero mean and a varying standard deviation. As a different sensor error value was selected at random for each time step from this normal distribution, the sensor error at a certain time t during the simulation run was independent from the sensor error of the next simulation time step t+0.1 seconds. This might not be the case for sensors (Waller, Simonin and Dance, 2003; Rigtorp, 2010) as their error values sometimes can be temporally auto-correlated. Additionally, whether the real-world sensor error values follow the normal distribution is unknown. Nevertheless, the methodology used for the modelling of the sensor error in this thesis is transferable; Any potential real-world sensor error distribution can be integrated within the framework presented and the results can be interpreted accordingly.

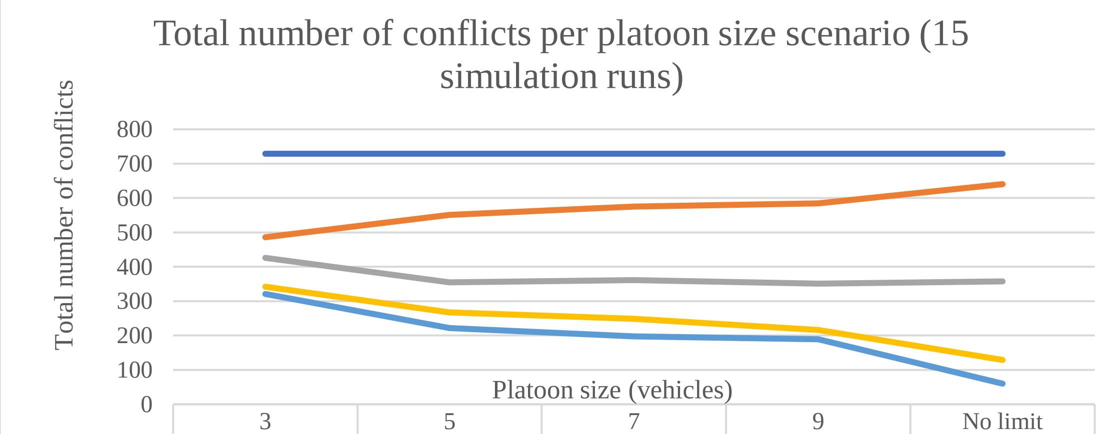
6.2.4 Platoon size scenario results (Scenarios 45 to 61)

As described in the literature review chapters, a number of studies have indicated that platoon size is a variable that affects the traffic flow dynamics of a motorway and could potentially affect traffic safety (Varaiya, 1993; Jiang, Li and Shamo, 2006; Zhao and Sun, 2013). The last set of scenarios investigated in this thesis are scenarios in which the CAV platoon size varies.

The platoon sizes used were the sizes of 3, 5, 7, 9 and the baseline scenario which had no platoon size limit. These values were selected as they were in line with Zhao and Sun, (2013) who investigated the impact of platoon size on traffic capacity. The change in the number of conflicts per platoon size and market penetration scenario are presented in Figure 6.7 and the percent change in the number of conflicts is presented in Table 6.8.

Table 6.8 Percent change in the number of conflicts per platoon size scenario

CAV market penetration rate	Platoon size				
	3	**5**	**7**	**9**	**No limit**
0%	0.00%	0.00%	0.00%	0.00%	0.00%
25%	-33.33%	-24.42%	-21.12%	-19.75%	-12.14%
50%	-41.56%	-51.30%	-50.48%	-51.85%	-50.91%
75%	-53.09%	-63.37%	-65.84%	-70.37%	-82.30%
100%	-55.97%	-69.55%	-72.84%	-74.07%	-91.77%



	3	5	7	9	No limit
0%	729	729	729	729	729
25%	486	551	575	585	640.5
50%	426	355	361	351	357.9
75%	342	267	249	216	129
100%	321	222	198	189	60

Figure 6.7 Total number of conflicts per platoon size scenario

Figure 6.7 can be interpreted in two ways; Firstly, by examining the results per market penetration rate and secondly by examining the results by platoon size. Starting to examine these results by market penetration rate, it is obvious that as market penetration rate increases, the number of conflicts is reduced significantly which is in line with the results from previous scenarios so far. However, the most interesting insights are derived when the results are interpreted within the same market penetration rate.

In more detail, at the 25% market penetration rate, an increase in the number of conflicts is observed as the platoon size increases. This result is surprising at first but it can be comprehended as follows: After observing the simulation environment, this increase in conflicts could be explained by the fact that the human-driven vehicles (75% of all traffic) could navigate more safely when the platoon size is 3 compared to when it is 5 or higher. In addition, a relatively long platoon may cause disruptions in traffic dynamics such as restraining human-driven vehicles to make lane change manoeuvres, especially near the diverging areas of the motorway. A larger increase is noticeable when the platoon size increases from 3 to 5 than when the platoon size changes from 5 to 7 and 9 consecutively. This can be explained by the fact that in this market penetration rate (25%), the formation of platoons with 5 or more vehicles is a rare occasion due to the small relative numbers, hence the safety results are similar. The results of the 25% market penetration rate are presented graphically in Figure 6.8. From this figure, it is obvious that the number of conflicts increases as the platoon size increases. Noticeably, once again, a high number of conflicts is concentrated in the merging and diverging areas of the motorway a problem which was identified in the results of sections 6.2.1 and 6.2.2 as well.

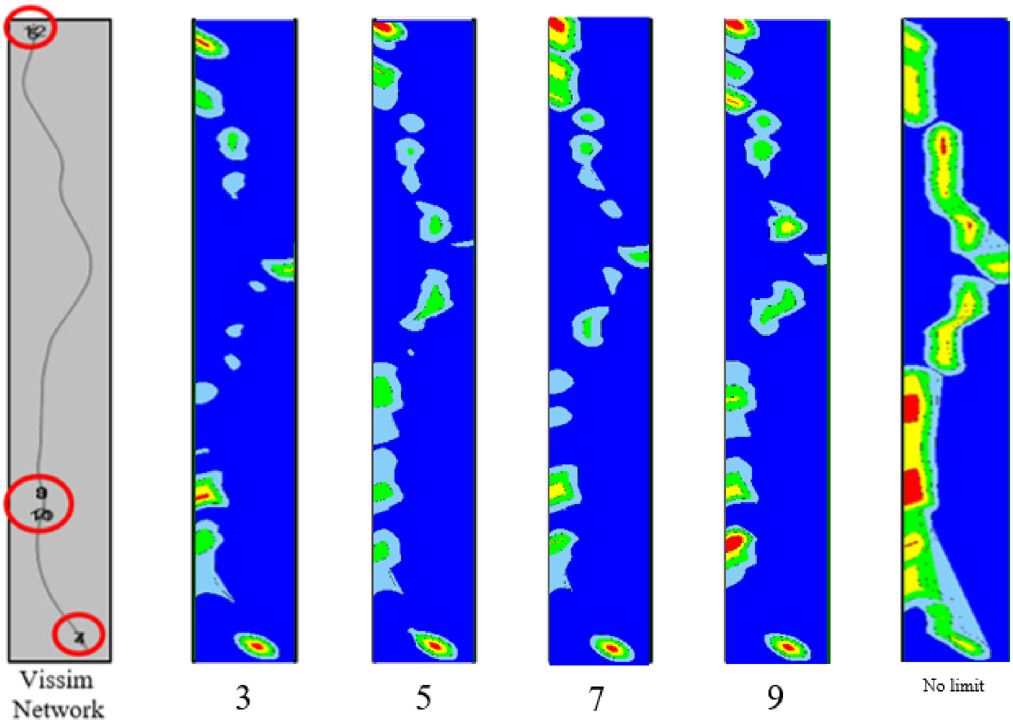


Figure 6.8 Heatmap of traffic conflicts in the 25% CAV market penetration scenario as the platoon size increases

At the 50% market penetration rate, a safety benefit is observed when the platoon size increased from 3 vehicles to 5 vehicles which can be interpreted with the fact that as one out of two vehicles in the network is a CAV, a larger amount of space in the motorway is saved due to the formulation of vehicle platoons. Consequently, manoeuvring vehicles in the motorway would find more available space to perform their lane changing manoeuvres or diverge and merge in the motorway. However, as the platoon size increases from 5 to 7 and 9 and the no platoon size limit scenario, no statistically significant difference in the number simulated conflicts is observed. This observation is confirmed by using the Kruskal-Wallis test (see section 6.2.3). The descriptive statistics of the samples used for the Kruskal-Wallis test are presented in Table 6.9 where the average number of conflicts per scenario is presented along with the standard deviation of the number of conflicts among all simulation runs. The p-value of the statistic of the Kruskal-Wallis test was 0.911 which indicated that the difference in the number of conflicts between these scenarios was not significant.

Table 6.9 Descriptive statistics of the samples used in the Kruskal Wallis platoon size

CAV market penetration rate	Platoon size			
	5	7	9	No limit
50% (mean, sd)	(23.66, 3.08)	(24.06, 3.16)	(23.40, 2.81)	(23.86, 2.96)

When CAV market penetration rate reaches 75% and 100%, a steady safety improvement is observed as the platoon size increases which reaches 91.77% at the 100% market penetration rate of the no platoon size limit scenario. That implies that, when CAV market penetration rate reaches 75% and higher, the impact of the platoon in the motorway in terms of safety is immense. As almost all vehicles are organised in vehicle platoons, the occupancy rate of the motorway is smaller, allowing for free space for manoeuvring, ultimately reducing the amount of vehicle interactions that could potentially be proven dangerous. It must be underlined that in the scenarios analysed in this section the lanes that the platoons were formulated was stochastic, and hence an equal distribution of vehicle platoons in the lanes is assumed.

Table 6.10 presents the descriptive statistics of the TTC values observes in the conflicts of each CAV platoon size scenario. Similarly to the corresponding results presented in sections 6.2.1, 6.2.2 and 6.2.3, it is observed that as market penetration rate increases, the mean value of the TTC increases. This implies that once again, less conflicts with TTC values close to zero are observed as the market penetration rate increases, which means that the number conflicts created as a result of a simulation environment flaw (see section 6.2.1) decreases. As vehicle platoon size increases no clear pattern can be identified in the change mean value of the TTC surrogate safety measure.

Table 6.10 Descriptive statistics for the Time to Collision observed in conflicts per platoon vehicle size scenario

Scenario Platoon size (market penetration rate)	TTC Descriptive statistic			
	Min	Max	Mean	Variance
3 (25%)	0	1.5	0.18	0.19
3 (50%)	0	1.5	0.29	0.26
3 (75%)	0	1.5	0.33	0.28
3 (100%)	0	1.5	0.69	0.4
5 (25%)	0	1.5	0.16	0.14
5 (50%)	0	1.5	0.25	0.23

5 (75%)	0	1.5	0.32	0.28
5 (100%)	0	1.5	0.62	0.39
7 (25%)	0	1.5	0.14	0.14
7 (50%)	0	1.5	0.39	0.34
7 (75%)	0	1.5	0.49	0.32
7 (100%)	0	1.5	0.72	0.39
9 (25%)	0	1.5	0.16	0.13
9 (50%)	0	1.5	0.21	0.19
9 (75%)	0	1.5	0.37	0.29
9 (100%)	0	1.5	0.75	0.38

The results presented in this section cannot be directly compared to the literature as the assessment of platoon size on motorway safety is a research gap that is identified in the literature section of this thesis. They should be interpreted along with the assumptions of the CAV platoon formulation algorithm. In this thesis, CAVs are allowed to join a platoon only from the rear – end of the platoon which is assumed to be the most common practice for a motorway scenario. Moreover, there is no empirical evidence to support the use of intra-platoon and inter-platoon spacing values of 0.6 seconds and 3 seconds accordingly which are used for this thesis. However, these values are used and proposed in existing literature.

The results presented in this section could provide useful insights regarding the real-world CAV implementation strategy on motorways. According to Figure 6.7, there is no consensus on a single value of platoon size that would provide the greatest safety benefit across all market penetration rates. To elaborate, the optimal platoon size (the platoon size that would provide the greater safety benefit) depends on the CAV market penetration rate. For example, platoon size 3 provides the greater safety benefit than the other platoon sizes in low CAV market penetration rates (25%) whereas, a platoon size with 5 or more vehicles can provide better safety benefit as CAV market penetration rate increases.

6.3 Statistical Modelling Results

In all the simulation results discussed in section 6.2, the number of conflicts for each tested scenario is presented. However, it is important to understand the reasons, factors or explanatory variables behind the occurrence of traffic conflicts in a microsimulation environment. It is impossible to identify these explanatory variables and the way that they affect the number of traffic conflicts through traffic microsimulation only. By employing the methods and the dataset discussed in section 4.3.3 and 5.4 respectively, a number of statistical models are developed. Through these models, it is possible to quantify the functional relationship between the dependent variable, the number of hourly traffic conflicts per motorway segment with a number of explanatory variables such as standard deviation of speeds, traffic flow, segment geometrical characteristics and market penetration rate. In order to facilitate the analysis, in this stage of the analysis, only data coming from scenarios 11 to 15 (Wednesday model – which is considered to be a typical weekday) with a higher disaggregation level in terms of market penetration rate (10% interval) are used.

At this point it needs to be emphasized that the exact functional form of the relationship between the dependent variable - conflicts, and the explanatory variables are not a priori known (Qin, Ivan and Ravishanker, 2004). There is no clear evidence that this relationship is linear and an assumption like this can lead to non-realistic estimates and conclusions. Hence, for the analysis in the thesis a number of transformations was considered, and the different independent variable combinations arising from the different transformations were tested. The form of the independent variables tested were linear, squared and logarithmic where this was feasible (non-negative or zero values). Dummy variables such as the variable “merging” which described whether a segment of the motorway was a merging section were not transformed. Only the results using the transformations which produced the most parsimonious model are presented in this section.

Before the start of the modelling of traffic conflicts, the correlation between the possible independent variables was examined. The inclusion of a pair of independent variables in which the collinearity problem exists may significantly affects the results and conclusions of the statistical model. Hence, the Pearson correlation coefficient results are presented in Table 6.11. The value of a negative Pearson correlation coefficient can vary between -1 and 1 and its equation is presented in equation (6.2) .

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(x_i - \bar{y})^2} \qquad (6.2)$$

where x_i and y_i are the individual observations and $\bar{x}$, $\bar{y}$ the corresponding means. A value of -1 demonstrates a perfect negative correlation whereas a value of 1 demonstrates a perfect positive correlation. The threshold for the Pearson correlation coefficient so as to classify a pair of variables as correlated is decided to be 0.8. Hence the problematic pairs in terms of correlation pairs are identified in Table 6.11 in bold fonts.

Table 6.11 Correlation matrix for independent variables used in the statistical models

	avgspeedseg	speed1	speed2	Speed 3	Avg speed global	Std speed2	Std speed 3	flow2	flow
flow3	-0.036	0.041	0.017	-.182	-0.074	-.110	-.301	.427	**.844**
flow2	-.733	-.709	-.688	-.758	-.764	**-.810**	**-.829**	1	.486
flow1	.755	.769	.749	.691	.759	.733	.685	-.420	.425
stdspeed3	**.856**	**.848**	.799	**.866**	**.851**	**.946**	1	**-.829**	-.170
stdspeed2	**.924**	**.937**	.881	**.888**	**.927**	1	.946	**-.810**	-0.016
avgspeedglobal	**.98**	**.958**	.975	**.945**	1	**.927**	.851	-.764	0.043
stdspeed1	.559	.651	.467	.506	.507	.722	.681	-.517	0.053
speed3	**.971**	**.907**	.953**	1	**.945**	.888	**.866**	-.758	-0.061
speed2	**.989**	**.952**	1	**.953**	**.975**	.881	.799	-.688	.129
speed1	**.977**	1	**.952**	**.907**	**.958**	**.937**	**.848**	-.709	.145
avgspeedseg	1	**.977**	**.989**	**.971**	**.980**	**.924**	**.856**	-.733	0.078

As discussed in the method section, when examining data which are produced by neighbouring areas -in this thesis neighbouring motorway segments- often, a problem of spatial autocorrelation occurs which needs to be taken into consideration when attempting to model the dependent variable. In order to prove the existence of spatial autocorrelation one should calculate the Moran's I test. Hence, the spatial autocorrelation of the number of conflicts between neighbouring motorway segments was tested using a global Moran's I which measures similarities and dissimilarities in observations across space. The Moran's I statistic is calculated based on the following equation:

$$I = \frac{N}{W} \frac{\sum_i \sum_j w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_i (x_i - \overline{x})^2} \qquad \textbf{(6.3)}$$

Where N is the number of spatial units indexed by i and j, x the variable of interest and $\bar{x}$ its mean; w_{ij} a spatial weights matrix as described in section 4.3.3 and W the sum of all w_{ij}. The value of Moran's I calculated for the dataset of this thesis is 0.40 with a standard error of 0.01793 which indicates the presence of spatial autocorrelation in the dataset.

For the purpose of this thesis several models which take into account spatial autocorrelation are developed using the Gibb's sampling method (known as the WinBugs statistical software) which allows the development of Bayesian models and calculates the coefficients of the model based on the Markov Chains Monte Carlo Simulation method.

After removing all the insignificant independent variables and taking into consideration the correlated pairs of them, the following Bayesian hierarchical negative binomial model is calculated. The general equation of this model is described in section 4.3.3. equation (4.29) and is adapted for the purpose of the thesis to include a random intercept term which describes similarities at the motorway segment level;

$$\ln(\mu_i) = \ln(t_i) + (b_0 + bX_i) + SC_i + UH_i + L_j \qquad \textbf{(6.4)}$$

where L_j is the random intercept at the motorway segment level and the rest described in section 4.3.3.

To derive the final posterior distributions of the coefficients of the model above, the model was run using 3 Markov chains. Initially 10,000 iterations as a warm-up for the model and consequently another 100,000 were conducted using the 3 chains in order to obtain a final set of posterior estimates. After this number of iterations the chains seemed to converge to the values of the coefficients. The estimates of the significant variables are presented in Table 6.12.

Table 6.12 Estimation results for traffic conflict Bayesian hierarchical model with spatial autocorrelation

Conflicts	mean	sd	MC error	2.5% percentile	97.5% percentile
Market Penetration Rate	-0.01896	0.001615	2.82×10^{-5}	-0.0221	-0.0158
Standard Deviation of Speeds between lanes	0.2688	0.06721	0.00016	0.1336	0.398
Spatial Correlation s.d.	0.1306	0.1068	0.004254	0.02441	0.4457
Segment i.d. random intercept s.d.	0.7352	0.06183	0.001425	0.5972	0.8468
Unobserved heterogeneity s.d.	0.05894	0.03523	0.00237	0.02467	0.1504
Constant	0.9335	0.1998	0.008859	0.5689	1.29
DIC= 2066.93, pD = 50.24, $\bar{D}$= 2016.69					

Initially by observing the results of the table above, one can notice that the coefficient of the exposure variable is missing from the original equation of the model. This is because the effect of the exposure variable in the models developed was proven to be insignificant. This result is logical since approximately the same amount of traffic flow runs through these sections hence, the variable flow didn't vary in a statistically significant way across the motorway segments.

As can be seen from Table 6.12 the posterior means for the standard deviation of spatial correlation (SC) is 0.73 and is statistically significant, suggesting that traffic conflicts are spatially correlated among neighbouring motorway segments. However, the value is low compared to other studies employing this method (Quddus, 2008). Similarly, the standard deviation of the random intercept at the segment level and the unobserved heterogeneity are also statistically significant.

The effect of the CAV market penetration rate is negative meaning that as the market penetration rate increases the conflicts decreases which is in line with the results presented in section 6.2. In order to calculate the actual effect of the market penetration rate one should employ the measure of elasticity since the relationship between conflicts and market penetration rate is logarithmic-linear. Hence the formula of elasticity b*$\bar{x}$ is employed to calculate an elasticity value of -0.95 which means that if CAV market penetration rate increases by 1%, then the amount of average conflicts in the segment would decrease by 0.95%. This observation can be visually confirmed by observing Figure 6.9. A downward trend can be observed in traffic conflicts as market penetration rate increases and some significant spikes are observed in traffic conflicts in certain segments.

Standard deviation between lanes seems to affect the number of conflicts per segment. Even though this result cannot be directly compared to the existing literature, because the majority of the literature is processing accident data, the standard deviation of speeds has been proven to have a positive coefficient when used for the modelling of accidents (Taylor, 2000; Quddus, 2013). In this thesis, standard deviation of speeds between lanes has a positive coefficient as well, which can be interpreted as follows; as the standard deviation of speeds between lanes increases by 1 km/h, the logarithm of traffic conflicts increases by 0.27. This result seems logical, as speed differences across lanes lead to more overtakes in adjacent lanes a fact which increases the possibility for a potentially dangerous incident to occur.

The absence of the dummy variable describing whether the segment is a merging or diverging area from the list of significant variables is surprising at first if one considers the conclusions of the simulation results above. The motorway merging areas are generally conflict hotspots where vehicles utilise an acceleration lane to merge according to the prevailing traffic conditions (e.g. speed and traffic flow) in the main carriageways. Inevitably, there are larger speed differences between lanes in these areas as the accelerating vehicles start from slower speeds in order to reach the average value of speed of the motorway. Hence, it is considered that the effect of the presence of an merging area is captured by the standard deviation of speeds between lanes. This conclusion can be confirmed by observing Figure 6.9 and Table 6.13. In the graph depicting the relationship between standard deviation of speeds between lanes and segment id significant spikes can be observed at around segment id number 4, 40 and 54. These segments were merging segments which represented junctions 21, 20 and 19 merging areas accordingly.

Table 6.13 Group statistics for standard deviation between lanes for merging and non merging areas

Group Statistics for Standard deviation of speeds between lanes					
		N	**Mean**	**Std. Deviation**	**Std. Error Mean**
Merging	1	44	2.05	1.040	.157
	0	550	1.60	.808	.034

For comparison purposes the simple hierarchical negative binomial model without the spatial autocorrelation effect is presented below. The simple model presented in Table 6.14 seems to have quite similar results with respect to estimated model parameters when compared with the hierarchical Bayesian model. The DIC value of the simple model is slightly higher than the one from the spatial model which means that it is not the best fitting model.

Table 6.14 Estimation results for the hierarchical Bayesian model without spatial correlation

Conflicts	**mean**	**sd**	**MC error**	**2.5% percentile**	**97.5% percentile**
Market Penetration Rate	-0.01893	0.001635	3.64×10^{-5}	-0.0224	-0.01583

Standard Deviation of Speeds between lanes	0.263	0.06689	0.00201	0.1316	0.3976
Segment i.d. random intercept s.d.	0.7519	0.04867	0.001306	0.6618	0.8525
Constant	0.9446	0.1975	0.006728	0.5618	1.336
DIC= 2067.13, *pD* = 50.27, $\bar{\boldsymbol{D}}$= 2016.85					

Finally, Figure 6.9 presents the scatterplots of the key variables in the statistical analysis; traffic conflicts, standard deviation between lanes, segment ID and CAV market penetration rate. Most of the scatterplots have been discussed above. However, the two bottom scatter plots remain to be discussed which describe the standard deviation of speeds between lanes as a function of the segment ID and market penetration rate. There is a clear decrease in the range of the standard deviation as vehicles proceed to the motorway. This might be due to CAVs identifying adjacent CAVs and forming vehicle platoons. Finally, the standard deviation between lanes shows an interesting curve as market penetration rate increases. As CAV market penetration rate reaches 30% there seems to be an average increase which might be a result of low speed vehicle platoons, but a significant downward trend is observed after the 30-40% market penetration range.

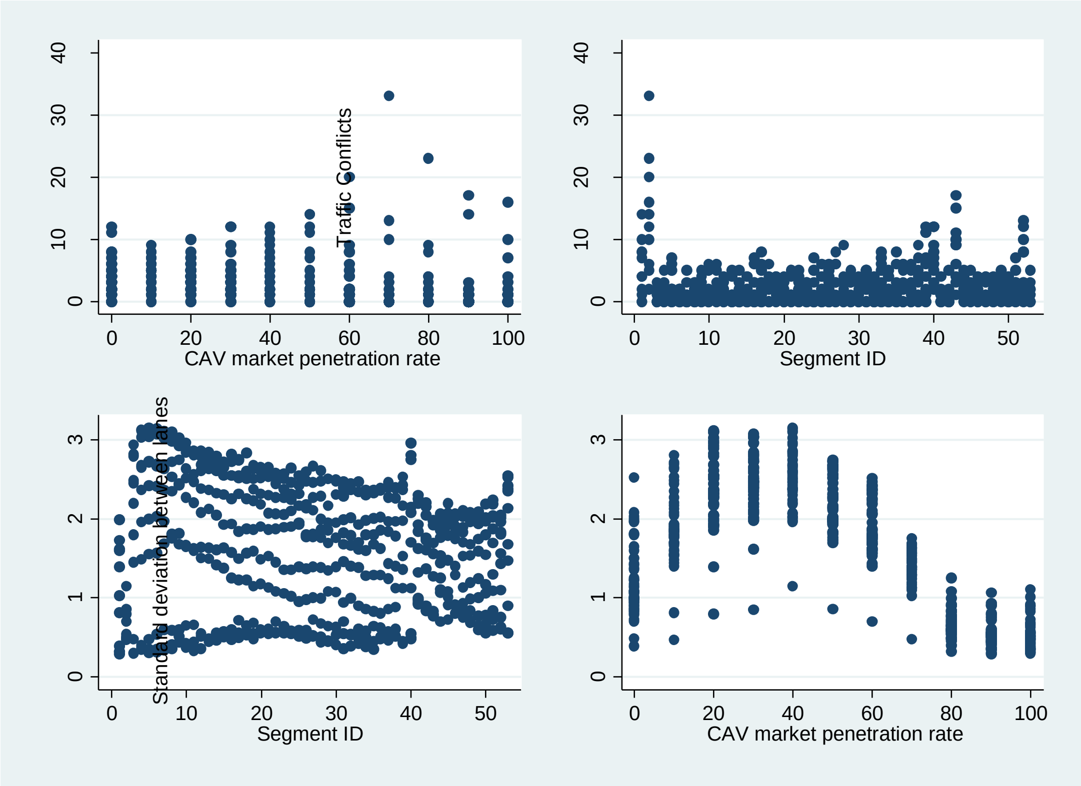


Figure 6.9 Graphs of traffic conflicts and standard deviation between lanes in comparison with CAV market penetration rate and segment ID

6.4 Comparison of the Simulation Framework and Statistical Modelling Results

This chapter of the thesis so far presented the results derived by the methods described in Chapter 4. This section will compare the results and findings of the two main sections of this chapter; the simulation framework results and the statistical modelling results on a common base (the RBDMA, sensor error and platoon size scenarios are not discussed in this section). The traffic simulation framework and the statistical modelling approach employed in this thesis are two methods which are significantly heterogeneous. Traffic simulation relies on a set of mathematical equations to describe the behaviour of individual vehicles inside a simulated road network, while statistical modelling attempts to model a given variable as a function of the variables contained in a specific dataset.

The statistical models were estimated using simulated data produced from the simulation framework, so one could argue that the results and conclusions could not possibly be different. However, the aim and purpose of statistical modelling is to identify hidden patterns within datasets which cannot be observed by just plotting the simulation output.

To put this in context, the statistical models identified a significant spatial autocorrelation pattern within the traffic conflict dataset which was not obvious from just observing the total number of conflicts produced by SSAM or by observing the heatmaps (e.g. Figure 6.3). Additionally, from the same heatmaps it was obvious that the merging areas of the motorway were conflict hotspots; areas where a high number of conflicts are concentrated. However, this result was not directly confirmed by the statistical results as the dummy variable which described whether a motorway segment was proven to be insignificant. On the other hand, this effect of the merging areas was captured by one of their defining characteristics; the standard deviation of speeds between lanes. Without the use of statistical analysis this result would not have been identified.

On the other hand, the statistical results agreed on the effect of CAV market penetration rate on the number of traffic conflicts. Both methods indicated that as CAV market penetration rate increases the number of conflicts decreases. However, by using the parameter estimates produced by the statistical modelling one could calculate the predicted reduction of conflicts for any given market penetration rate. For instance, according to the coefficients calculated, at the 15% market penetration rate, in segment number 2 the predicted number of conflicts is 3.28.

To conclude, the two methods used in this thesis proved to be complementary to each other in terms of results. Without the simulation framework to produce the traffic conflict dataset, the statistical modelling would not have been possible. Accordingly, without the statistical modelling certain patterns in the occurrence of traffic conflicts such as the importance of standard deviation of speeds between lanes within a traffic microsimulation scenario would not have been identified.

6.5 Policy Recommendations and Practical Implications

One of the objectives of this thesis identified in Chapter 4 (section 4.2) is to recommend a number of specific scenarios when the safety impact of CAVs would be maximized. Using the results presented in this chapter, a number of recommendations can be made. Additionally, this section will discuss the applicability of the methodology applied in this thesis to evaluate other conflicting CAV scenarios.

Throughout all the simulation results and the statistical results, it is observed that specific segments of the motorway are hotspots for traffic conflict occurrence. ; areas where a larger number of conflicts is observed. This observation was consistent throughout all the studied scenarios. A similar finding was indirectly confirmed by the statistical results which indicated that the standard deviation of speeds between lanes significantly affects the number of conflicts. The varying platoon size scenarios indicated that long platoons travelling in the outermost lane of the motorway could potentially block other vehicles from exiting the motorway, especially in the low market penetration rates. According to the above, a need to re-evaluate the design of the motorway merging and diverging areas so as to accommodate the challenges arising by the implementation of CAVs. By designing an environment where a smoother integration to the traffic stream of the motorway is ensured, the number of conflicts might be reduced. A possible way to do that would be to enlarge the length of the acceleration or deceleration lanes in order to ensure that the sufficient lateral gap can be identified through the prolonged merging process.

On the other hand, encouraging results were derived for the readiness level of existing vehicle equipment. The sensor error scenarios indicated that current sensor error rates do not significantly affect the number of traffic conflicts. However, this result must be interpreted according to the underlying assumptions that sensor errors are uncorrelated and normally distributed. If a more appropriate error distribution is provided by original equipment manufacturers, using the method presented in this thesis, its impact on the occurrence of traffic conflicts can be evaluated.

Several useful insights are derived by the platoon size scenario results. In order to maximise the safety impact of CAVs, the correct platoon size should be implemented at the correct time. To elaborate on this, it was indicated that when the market penetration rate of CAVs was around 25%, a platoon larger than 3 vehicles caused more traffic conflicts. This problem was observed mainly because large platoons consisted the manoeuvring of vehicles in the motorway difficult. On the other hand, when market penetration rate reached 50% and more, as the platoon size increased it provided a reduction of conflicts. The exact market penetration rate percent which provided the first positive effect on the number of traffic conflicts was not identified in order to provide a break point. However, according to the above, should a platooning scheme be employed in UK motorways it is recommended that the optimal platoon size should not be a constant number, but it should vary according to the real-time market penetration rate of CAVs. Especially during the transition period, the market penetration rate of CAVs might vary significantly and a constant real-time monitoring of the motorway might be needed to ensure that safety is maximised in real time.

Finally, the method presented in this thesis and namely; the traffic microsimulation software, the calibration and validation process and the CAV modelling technique is highly flexible. By appropriately adapting the code presented in Chapter 4 and with basic traffic modelling knowledge, a road operator such as Highways England who is the company operating the strategic road network, or a local / governmental authority, could attempt to evaluate the impact of CAVs on a number of conflicting scenarios arising from motorway operational challenges. It must be noted however, that the scenarios that can be tested are naturally limited by the capabilities of the simulation software and the accompanying C++ code. Possible interesting scenarios could be a lane closure due to an accident or a dedicated lane for CAVs. The impact calculated could be not only in terms of safety, but also traffic performance (traffic capacity, travel time etc.) and environment (vehicle emissions).

6.6 Summary

Section 6.2 presented the results of the traffic microsimulation framework in terms of the conflicts calculated through SSAM by using the vehicle trajectory files produced by VISSIM. CAVs were represented in the simulation framework according to the CAV behaviour algorithm described in chapter 4 of this thesis. Several scenarios were tested based on various traffic flow values of a motorway network and fundamental operational and technological challenges arising from the implementation of CAVs in motorway environments;

a) Weekday scenarios representing different traffic flow values
b) Route-based decision-making algorithm (RBDMA) scenarios

c) Sensor error scenarios
d) CAV platoon size scenarios

The main findings of the weekday scenarios are:

- A great reduction of traffic conflicts is observed as the market penetration rate increases across all different traffic flow values tested;
- The safety performance of CAVs improves at 25% market penetration rate as traffic flow values increases;
- A relatively smaller improvement is observed from 75% to 100% market penetration rates
- A large concentration of traffic conflicts is observed at motorway merging areas
- The mean TTC value for conflicts increases as market penetration rate increases

The main findings of the RBDMA scenarios are:

- The RBDMA reduces the number of conflicts furthermore when compared to the no-RBDMA scenario
- The reduction of conflicts when compared to the no-RBDMA scenario becomes larger as market penetration rate increases
- The mean TTC value for conflicts increases compared to the no-RBDMA scenario as market penetration rate increases

The main findings of the sensor error rate scenarios are:

- Sensor error rates found in existing vehicle equipment does not affect the number of conflicts calculated through traffic microsimulation significantly

The main findings of the platoon size scenarios are:

- At the 25% market penetration rate, the number of traffic conflicts increases as the platoon size increases
- At the 50% market penetration rate, the number of traffic conflicts is reduced when the platoon size increases from 3 to 5 vehicles and remains constant between platoon sizes of 5,7 and 9 vehicles

- At the 75% and 100% market penetration rates, the number of traffic conflicts is reduced significantly as the platoon size increases

Following, section 6.3 presented the results of the traffic conflict statistical modelling. A hierarchical Bayesian negative binomial regression model was developed which could take into account spatial autocorrelation of conflicts and unobserved heterogeneity. The traffic conflicts were modelled as a function of the traffic characteristics of the corresponding motorway segment.

The main findings of the statistical model developed are:

- The spatial autocorrelation term is significant in the model which indicates similarities in traffic conflict observations between neigbouring motorway segments
- CAV market penetration rate is linked with the number of conflicts with a negative significant coefficient; as market penetration rate increases, the number of conflicts decreases
- Standard deviation of speeds between lanes is related with the number of conflicts with a positive significant coefficient; as the standard deviation of speeds in the motorway segment increases, the number of conflicts increases as well
- The effect of the merging areas of the motorway is captured within the standard deviation of speed variable

7 Conclusion

7.1 Summary

CAVs are a rapidly advancing technology which is believed to radically change the society as we know it, promising to bring a great benefit in many impact areas such as traffic, road safety and the environment. CAVs are at the doorstep of real-world implementation and several real-world trials are being conducted worldwide. Despite these trials, the aforementioned benefits have not been quantitatively calculated, as real-world data are not widely available.

This is the reason why current literature has concentrated its focus on simulation in order to evaluate their impacts, which seems to be the only available alternative as of today. CAVs are complex and simulating them is a difficult task. Most studies are either developing complex simulation frameworks which do not facilitate the collection of significant results or are focusing only on specific characteristics of CAVs without including several operational, tactical, strategical and technological issues arising from the real-world implementation of CAVs. Concerns about these issues exist in another part of the literature, such as the reliability of existing vehicle equipment found in CAVs (i.e. radars, lidars) or the real-world implications of vehicle platoons. However, these challenges have not yet been investigated within an integrated CAV simulation environment.

This research attempted to evaluate the safety impact of CAVs by developing an integrated CAV control algorithm which can address the aforementioned challenges. For this purpose, initially, a part of the M1 motorway in the United Kingdom between Junctions 19 and 21 is designed within the traffic microsimulation software VISSIM according to the real-world geometry of the motorway. The human driver model is calibrated and validated in two stages. In the first stage, minute-level real-world inductive loop detector data are used in order to calibrate the baseline models in terms of traffic characteristics. The inductive loop detector data are processed in order to calculate the variables traffic flow, speed distribution and time headway which are used as input to the simulation models. The simulation output is compared with the real-world data in order to ensure that fundamental traffic flow metrics such as travel time and traffic flow are accurately represented in the model. The results of the first stage calibration indicated that no adjustment was needed to the default Wiedemann 99 car following model parameters.

The second stage of the calibration process involved the use of primary data collected with the instrumented vehicle of Loughborough University. Fifteen real-world trips were performed in the study area in order to form the dataset needed for the safety-oriented calibration. Through the collected data, several Time-to-Collision (TTC) to the leading vehicle distributions were calculated. These distributions were compared with simulated TTC distributions which calculated through an external application programming interface, as TTC distributions are not provided by default in VISSIM. The results of this stage of the calibration indicated that the real world TTC distributions were significantly different from the simulated TTC distributions. Consequently, a sensitivity analysis was performed to maximise the U value of the Mann-Whitney statistic test that was performed to examine the difference between the two distributions. Through this process, the value of the Wiedemann car following model parameter CC3 which is the threshold when a vehicle enters following mode in VISSIM was changed from 8 to 5 seconds.

The CAV driving behaviour was programmed in C++ programming language using the aforementioned External Driver Model API. The behaviour aimed to represent all subsystems of CAVs. More specifically, the sensing and perception subsystem was programmed to include sensor measurement errors and the range of the sensors of the vehicles was programmed to be 200 meters according to values found in existing literature. The planning and control subsystem were represented with a route-based decision-making algorithm (RBDMA) which assigned CAVs in the corresponding lanes according to their destination and a longitudinal control and lateral decision-making algorithm which ultimately led to the formulation of vehicle platoons. The formulation of the vehicle platoons was dictated by a set of rules which arise from motorway operations and existing literature. The longitudinal time gap in platoons was decided to be 0.6 seconds while for lane changing manoeuvres the required minimum time gap was decided to be 0.6 seconds from the preceding and the following vehicle.

The CAV driving behaviour was assigned to a specific vehicle type in VISSIM and several market penetration scenarios were tested along with a number of weekday (aiming to represent different traffic flow values) sensor error, platoon size and RBDMA scenarios.

The safety benefit of CAVs was evaluated using traffic conflicts – situations where a collision would occur between two vehicles if an evasive manoeuvre is not performed by one of them - as a key performance indicator. The conflicts were calculated through the Surrogate Safety Assessment Model, a tool which can process the vehicle trajectory files produced by VISSIM and identify traffic conflicts. The conflicts were identified based on surrogate safety measure thresholds (TTC and PET) and by projecting the location of the vehicles in time in order to confirm that the two vehicles were indeed on a collision course. SSAM subsequently, recorded all conflicts along with their location and a number of descriptive statistics for the surrogate safety measures. SSAM was able to produce the results for each of the traffic microsimulation scenarios mentioned in the previous paragraph.

The number of conflicts was matched according to their location with a corresponding motorway segment which was defined by two consecutive simulation data collection points. The result of this matching was a dataset containing the number of conflicts along with corresponding traffic measurements such as speed, standard deviation of speed, traffic flow as well as motorway geometry characteristics such as curvature measured as the number of spinal points observed in the simulation software. This dataset was used for the statistical modelling of traffic conflicts.

Initially, the simulation framework results by weekday indicated that as CAVs infiltrate the market, a greater safety benefit is observed. This safety benefit is increased in the 25% market penetration rate as the traffic flow values increase, whereas smaller improvement is observed when examining the 75% to 100% market penetration rates. However, overall the results seemed promising, as CAVs reduced traffic conflicts by 94.32% in the best-case scenario. The results highlighted the motorway merging areas as problematic in terms of traffic conflict concentration. A high number of conflicts was observed in the merging areas and this was also highlighted in the corresponding heatmaps. The results for these scenarios was in line with a part of relevant literature, however, most of the results were not directly comparable due to the significant differences in the underlying assumptions.

The results of the RBDMA scenarios indicated that a route-based coordination of a CAV fleet would lead to further improvement in terms of traffic safety as compared to the baseline Wednesday scenario an improvement of 18.56% to 25% was observed based on the CAV market penetration rate. However, a high number of traffic conflicts was observed in motorway merging areas again.

At first glance, sensor error was proven to not significantly affect the number of produced conflicts in the traffic microsimulation environment according to the results. This initial observation was confirmed by using a Kruskal-Wallis statistical test. This result seemed logical according to its assumptions, as the tested sensor error rates were small compared to the measured metrics.

The last set of simulation scenarios were the platoon size scenarios which provided interesting insights. Starting at 25% market penetration rate, traffic conflicts seemed to increase while the platoon size increased as, long vehicle platoons created problems in the vehicles attempting to manoeuvre around the motorway or vehicles attempting to exit. However, this problem seemed to improve at the 50% market penetration rate and further, since the motorway occupancy rate decreased due to the increasing number of platoons. Consequently, vehicle manoeuvring was facilitated and a steady decrease in conflicts was observed as the platoon size increased.

In order to validate the macroscopic observation of the simulation results and identify the underlying factors behind the occurrence of traffic conflicts in a traffic microsimulation environment, several statistical models were developed using the dataset discussed above. Since the traffic conflicts demonstrated a low mean, overdispersion and spatial autocorrelation, a hierarchical Bayesian negative binomial regression model was developed which took into account spatial autocorrelation and unobserved heterogeneity.

The statistical results identified that the spatial autocorrelation, the random intercept at the segment level and the unobserved heterogeneity (uncorrelated random effects) terms were statistically significant, a fact which added a new dimension to the simulation results. In comparison with the simulation results, the statistical results did not indicate the “merging” dummy variable (a variable which was 1 if the motorway segment was a merging area or 0 otherwise) as significant to confirm the findings directly. Instead, the standard deviation of speeds was identified to have a significant positive effect on the number of traffic conflicts, a result which was in line with relevant accident count modelling literature. After careful consideration it was discussed that the standard deviation of speeds captured the effect of the merging areas as these areas are characterised by high values of standard deviation of speeds. Finally, the market penetration rate was found to have a negative effect on the number of traffic conflicts which indicates that CAVs will indeed improve road safety as they penetrate the market.

A number of policy recommendations were derived from both the statistical and simulation framework results. Initially, the concentration of traffic conflicts in the motorway merging areas indicated the need to redesign these specific areas so as to ensure a smoother integration of vehicles into the traffic stream of the motorway. A possible enlengthening of the acceleration lanes could ameliorate the safety dangers. Additionally, as far as platoon size is concerned this thesis concluded that in order to maximise the safety benefit, the appropriate platoon size must be implemented at the correct point in time, if time can be expressed in terms of CAV market penetration rate. When CAV market penetration rate is around 25% a smaller platoon size would provide greater safety benefits while longer platoon sizes would be better as the market penetration rate increases further.

7.2 Contribution to Knowledge

This research has produced new methodological and quantitative outcomes which could be considered for future analyses. The main contributions to knowledge of this thesis are:

1. <u>The utilisation of microscopic real-world driving radar data for the safety-oriented calibration and validation of the traffic microsimulation model</u>

This thesis utilised microscopic real-world driving data collected through an instrumented vehicle to calculate a Time-to-Collision (TTC) distribution to the preceding vehicle. This distribution was compared with a TTC distribution calculated through data collected from individual vehicles within the simulation environment (VISSIM). Similar processes have been followed in the literature. Most of them however, calibrate the driver model in simplistic custom made simulation environments (e.g. Zhu *et al.*, 2018) which do not reflect fundamental challenges arising from motorway operations and usually focus on traffic key performance indicators. This thesis demonstrated that using the proposed method and the External Driver Model API tool of VISSIM the TTC distribution can be reconstructed, and the product can be directly compared to the corresponding real-world measurements. Most importantly, this method presented in this thesis is flexible, as it can be applied to calculate any safety metric which can be calculated with an equation utilising the data produced by VISSIM simulation vehicles. This method can be proven valuable when CAV data are available, as, using the same method the appropriate car following model can be calibrated with regards to safety.

2. <u>The modelling and effect of sensor error in a traffic microsimulation environment</u>

Addressing fundamental technological challenges arising by the implementation of CAVs in a traffic microsimulation environment was as a research gap identified in the literature review chapter and sensor error as well as sensor reliability was one of the most widespread technological concerns that have been expressed over the years. This thesis presented a method to program the sensor error as a normally distributed additive term to the measurements of the traffic microsimulation software which defined the longitudinal and lateral control of the vehicle. This behaviour aimed to simulate the behaviour of sensor error in the real world. The sensor error distribution contained justified assumptions based on literature, regarding the form of its statistical distribution and its temporally uncorrelated values. However, using the proposed methodology any distribution or pattern within the error can be simulated.

To the author's knowledge, the safety impact of sensor error has not been investigated before in an integrated traffic microsimulation environment. The testing of the aforementioned sensor errors added to the existing knowledge, by indicating that even though the public is concerned about sensor errors, they are not significantly large to affect the number of traffic conflicts in the simulated motorway environment.

3. <u>The safety impact of CAV platoon size in a motorway environment</u>

Even though the algorithms behind of platoon formulation in a motorway have been widely researched, the exact effect of platoon size on motorway safety had not been researched previously. The investigation of the safety impact of CAV platoon size conducted in this thesis increased the understanding about the impact of platoon size on traffic safety and thanks to this, a number of practical implications and policy recommendations were made. More specifically, the results indicated that in low market penetration rates (around 25%) a lower platoon size value (3) would improve motorway safety when compared with larger platoon size values (5, 7 or 9) as long vehicle platoons can cause disturbances in the traffic flow of the motorway, especially in the merging and diverging areas. Hence, the platoon size of 3 vehicles is proposed for low market penetration rates (<25%) whereas, at higher market penetration rates (>50%), even a platoon size greater than three vehicles could potentially reduce the number of conflicts even more. This can be explained by the fact that the increasing number of platoons formulating as the market penetration rate increases, can reduce occupancy percentage of the motorway (and consequently the free space for manoeuvring) and consequently create more space for manoeuvring. Last but not least, the same results indicated the need for a re-evaluation of the design standards of the motorway merging and diverging areas. A large number of conflicts was observed in these areas and a redesign is deemed necessary so as to accommodate CAVs safely.

4. <u>The utilisation of simulated traffic and conflict data for use in statistical modelling of traffic conflicts</u>

A significant amount of work has been conducted in the past to model accident counts and identify their explanatory variables. In addition to that, studies have attempted to derive a functional relationship between accident counts and traffic conflict counts, but so far there is a lack of studies investigating the underlying factors behind the occurrence of traffic conflicts in a traffic microsimulation environment. In order to tackle that, this thesis formulated a dataset containing traffic conflicts (produced by SSAM) arising from specific motorway segments along with corresponding traffic characteristics per market penetration rate. Using this dataset, a hierarchical Bayesian negative binomial model was developed, the results of which advanced the understanding of the occurrence of traffic conflicts;

Traffic conflicts were proven to be spatially correlated between neighbouring segments - a characteristic which is also present in accident data. Confirming the simulation results, the model indicated that conflicts appear to have a negative relationship with market penetration rate; as CAV market penetration rate increases the number of conflicts is reduced. Finally, the explanatory factor behind the concentration of traffic conflicts in the motorway merging areas was clearly shown to be the standard deviation of speeds between the lanes.

7.3 Study Limitations and Assumptions

The research presented in this thesis includes limitations and assumptions arising from methodological issues and the uncertainty overarching CAVs and their modelling. The most important ones are outlined below:

7.3.1 Traffic microsimulation limitations and assumptions

- **Choice of the simulation software:** The results of this thesis were produced using the traffic microsimulation software VISSIM. Even though the simulation model was calibrated and validated using real-world data, the results always reflect the underlying assumptions of the software. For example, the human driver is assumed to drive according to the Wiedemann 99 car following model.
- **Transferability of the Method** During the three years of this PhD project, similar tools to External Driver Model which was used to simulate CAVs were investigated (e.g. Aimsun next API). It was concluded that the equations presented for the car following CAV model presented in this thesis can be directly transferred to other software ultimately reaching similar results. Hence, it is concluded that the methodology presented can be transferable
- **Inductive loop detector data aggregation:** The inductive loop detector data used in this study to calculate the traffic flow, speed and time headway distribution were organised in minute level observations. However, they were averaged in order to create annual values which may not reflect special conditions arising from day to day incidents in the motorway
- **Limited instrumented vehicle data:** The instrumented vehicle data were used to calibrate the traffic microsimulation model in terms of safety, by calculating a TTC distribution. For this study, a limited number of trips were conducted with a limited number of drivers. A larger and more representative dataset could produce more reliable real world TTC distributions.

- **Simulation time of the day:** The baseline models developed in this thesis were programmed to represent the time of the day between 11-12:00 AM. The traffic flow values observed during this time of the day is relatively low compared to morning peak and afternoon peak traffic flow values. Hence, the corresponding results reflect the impact only during the examined times. The impact of CAVs during peak times could be significantly different and needs further investigation.
- **CAV longitudinal control:** This study assumed that all CAVs will follow the longitudinal control algorithm developed which is derived based on simple physics equations. However, this is an assumption which cannot be justified unless real world CAV data are available.
- **CAV lateral control:** This study assumed that should CAVs identify adjacent time gaps of 0.6 for lane changes, they could perform a lane change manoeuvre. The lane changing manoeuvre itself was controlled by VISSIM and no steering wheel control was implemented due to inherent complexity.
- **CAV sensor error:** CAV sensor error was programmed to be normally distributed and temporally uncorrelated. Different assumptions might have led to significantly different outcomes. Additionally, complete sensor error failure was not considered in this study as well as sensor error arising from different sensors such as camera or lidar.
- **Route-based decision-making algorithm:** This study proposed a route-based decision-making algorithm which aimed to coordinate CAVs in lanes according to their destination. Whether such an algorithm would be the optimal to be implemented in a real-world network is unknown. Hence, the corresponding results cannot be generalised or transferred.
- **Platoon size scenarios:** In the platoon size scenarios, CAVs where assumed to comply 100% with the given platoon size and only one size was tested per scenario. Additionally, only rear end platoon joining was considered and it was assumed that all CAVs would be able to form platoons with all other CAVs, something which might not be true due to differences in the underlying hardware and software.
- **Conflict identification and validation:** The number of conflicts produced by each scenario was produced by SSAM, hence the reliability of this number lies

on SSAM's validity. Additionally, the number of traffic conflicts was not validated directly using on-site conflict numbers but only indirectly using TTC distributions from the instrumented vehicle.

7.3.2 Statistical modelling limitations and assumptions

- **Temporal aggregation:** The dataset developed for the statistical model contained variable values which were averages calculated from the 15 simulation runs of the corresponding market penetration rate scenario. Such an aggregation level might conceal information related to exact traffic flow values and the occurrence of conflicts.
- **Omitted variables:** The models that have been developed did not control for a number of important explanatory variables which may affect the number of traffic conflicts such as light, weather, varying traffic flow and pavement condition. Such exclusion might have led to erroneous estimations.
- **Spatial and temporal transferability:** The statistical model was estimated based on simulated data and using the CAV algorithms mentioned above. Hence, its results are closely connected to the corresponding assumptions and they cannot be transferred or generalised. By calculating statistical models from more networks and CAV control algorithms the transferability of the proposed model could be justified.

7.4 Extensions and Suggestions for Future Research

The work that has been presented in this thesis is a promising and flexible approach that can easily be extended or adapted to accommodate the needs of a researcher. Hence, considering also the limitations discussed above, the following recommendations for improvement and extension can be made for future work.

The most fundamental improvement of the method presented in this thesis would be the use of CAV data to validate the developed CAV algorithm. A validated CAV control algorithm would add tremendous value to the research and would be able to calculate CAV impacts more reliably. However, it must be acknowledged that such data are extremely difficult to acquire. Once they are available however, several machine learning techniques such as deep reinforcement learning can be developed to train a simulation driver model or agent to mimic the CAV behaviour. The developed trained models can be directly input into the methodology presented in this thesis in order to simulate CAVs accurately without having to rely on assumptions.

Following, using the methodology presented in this thesis, a number of widely discussed in existing literature scenarios can be developed. Such scenarios can be infrastructure-based such as the investigation of segregated operation of CAVs in the motorway with isolated or integrated dedicated CAV lanes, or vehicle-based scenarios such as connectivity-based scenarios (packet loss or packet lag) or high traffic flow value scenarios (peak scenarios). Special focus should be given to cooperative fleet-based scenarios such as the RBDMA algorithm presented in this thesis. Similar scenarios could include the investigation of the impact of CAVs in motorway shockwave propagation or scenarios where CAVs would have to make a cooperative decision based on a motorway incident such as a lane closure or a stopped vehicle. Once again, rapidly advancing artificial intelligence techniques could be a valuable ally in the implementation of this kind of scenarios. For cooperative decision making for example, swarm intelligence might provide excellent foundation for development.

Future research should also consider alternative or more reliable ways to identify and predict conflicts in a traffic microsimulation environment. Using the API of VISSIM specific vehicle trajectory data can be extracted and subsequently used to derive a number of surrogate safety measures and evasive manoeuvre thresholds in order to identify a conflict. With that being said, if such a conflict identification and subsequently prediction algorithm is developed, it could potentially be implemented in individual vehicles within VISSIM in order to predict simulation conflicts and perform evasive manoeuvres in real time.

A more reliable definition of traffic conflicts could lead to a more reliable traffic conflict data. This consequently would affect the quality of the statistical output, which relies on the quality and detail of the conflict data. Hence, an improvement would be the temporal disaggregation of the conflict data, so as to investigate the effect of traffic flow on conflicts. Future conflict analysis should also investigate the inclusion of multivariate conflict analysis by grouping the conflicts according to their severity. The inclusion of additional parameters in the statistical modelling could also be investigated such as real-world geometry data or simulation weather data.

Finally, this thesis presented a methodology to identify the underlying factors affecting the safety impact of CAVs. Similar research should continue investigating them under different scenario specifications and assumptions so as to identify the set of challenges arising from their implementation in the real world.

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Appendix

Publications related to this thesis:

The following publications have been made in a peer-reviewed journal or presented at a conference as a result of this thesis:

Journal paper:

Papadoulis, A., M. Quddus, and M. Imprialou.(2019) Evaluating the Safety Impact of Connected and Autonomous Vehicles on Motorways. *Accident Analysis and Prevention*, Vol. 124, January, 2019, pp. 12–22. https://doi.org/10.1016/j.aap.2018.12.019.

Conference paper:

Papadoulis, A., Quddus, M., & Imprialou, M. (2018). Estimating the Corridor-Level Safety Impact of Connected and Autonomous Vehicles. In Transportation Research Board 97th Annual Meeting Proceedings.

Papadoulis, A., Quddus M., and Imprialou M.(2020) Modelling the safety impact of Connected and Autonomous Vehicles in simulation and statistics: Platoon size, Sensor Error and Path choice *in Proceedings of the 99th Transportation Research Board Meeting, Washington DC, United States*

C++ codes used in this thesis:

```
DRIVERMODEL_API int DriverModelSetValue
(long type, long index1, long index2, long long_value, double double_value,
char *string_value)
```

Code 1 Initialisation of the DriverModelSetValue function of the External Driver Model API

```
case DRIVER_DATA_VEH_ACCELERATION:
              ego_acc = double_value;
              return 1;
```

Code 2 Storage of the acceleration value in a user specified variable

```
DRIVERMODEL_API int DriverModelGetValue (long   type, long index1, long
index2, long *long_value,double *double_value,char **string_value)
```

Code 3 Initialisation of the DriverModelGetValue function of the External Driver Model API

```
std::random_device rd;

std::normal_distribution<double> distribution(mean, sd);

double sd =0.05;
       double mean = 0.05;

double error1 = distribution(rd);
```

Code 4 Random sensor error generation in C++ through a normal distribution

```
if (lanes_current_link == 3)

{if (next_link == 6 || next_link == 14 || next_link == 15 || next_link == 7)

{if (current_lane == 3)

active_lane_change = 0;

else if ((current_lane == 2 || current_lane == 1) && (di_11a > ego_speed*0.6 &&
di_1n1a < -sp_1n1a*0.6 && (id_11 > 0 || id_1n1 > 0) && ego_speed > 14.0))

active_lane_change = +1;}

if (next_link == 21 || next_link == 28)

{if (current_lane == 3 && (di_n11a > ego_speed*0.6 && di_n1n1a < -sp_n1n1a*0.6 &&
(id_n11 > 0 || id_n1n1 > 0) && ego_speed > 14.0))

active_lane_change = -1;

else if (current_lane == 2)

active_lane_change =/+1;

if ((Type[ID(01)] != 2 && Type[ID(n11)] == 2&& di_n11a > ego_speed*0.6 &&
di_n1n1a < -sp_n1n1a*0.6 && (id_n11 > 0 || id_n1n1 > 0) && ego_speed > 14.0) &&
current_lane == 1)

{active_lane_change = -1;}

if ((Type[ID(01)] != 2&& Type[ID(n11)] != 2&& Type[ID(11)] == 2 && di_n11a >
ego_speed*0.6 && di_n1n1a < -sp_n1n1a*0.6 && (id_n11 > 0 || id_n1n1 > 0) &&
ego_speed > 14.0) && current_lane == 2)

{active_lane_change = 1;}
```

```
{if ((Type[ID(01)] != 2&& Type[ID(0n1)] == 2) || (current_link == 1 ||
current_link == 2))

{active_lane_change = 0;}

}
```

Code 5 RBDMA Logic developed in the framework of this thesis

```
if (Type[ID(01] == 2 && di_01 < 200.0)

      {desired_acceleration = relspeed_01a*relspeed_01a/((x2 – x1)*2.0);}
```

Code 6 The CAV car following model developed in the framework of this thesis as appeared in the C++ code

```
#include <iostream>

ofstream TTC;

double TTC = 0.0;

TTC.open("C:\\Users\\...\\TTC.txt");

TTC=di_01/relspeed_01

TTC << relspeed_01 << "," << di_01 << "," << TTC_01 << "," <<   endl;
```

Code 7 The TTC extraction algorithm developed in the C++ code for this thesis